INNOVATIVE FUZZY PETRI NET MODEL FOR CHINESE MEDICINE EXPERT SYSTEM

by

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This work is dedicated to Jesus Chris.

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Abstract

Adapt a fuzzy petri net approach to construct a Chinese medicine knowledge-based expert System is an interesting research topic in both Chinese medicine and knowledge representation.

To better represent the Chinese medical knowledge, we have introduced a new component - *dynamic certainty factor* (DCF) to the current fuzzy petri net (FPN) model. This concept (DCF) is a novel evolution to the fundamental petri net model, which provide additional flexibility and new methodology to represent some unsolved problems.

In the current FPN representation, each transition would have a constant certainty value throughout the reasoning process. Independent of the fuzzy value of its antecedents, this certainty value always remains the same. Nevertheless, this certainty value is an important factor to determine the deduction during the reasoning process of a FPN model.

During our study, we have discovered that the current FPN model cannot represent the Chinese medical knowledge in a satisfactory manner. As a result, we evolve the current FPN model by introducing a dynamic certainty factor so that the traditional Chinese medicine knowledge can be processed by the FPN techniques. Besides, a new reasoning methodology is also introduced in order to provide more flexibility in our system.

論文題目：創新模糊 Petri 網的中國醫學應用
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撮要

此研究提目目的是將模糊 Petri 網應用在中國醫學範圍。
由於中國醫學跟西方醫學的基本概念、本質和觀點是不同的，所以我們這研究會跟據中國醫學的方向來改進現有的模糊 Petri 網，我們加入了一個創新的元素 — 動態可能性。這個創新的概念是由現有的模型演變出來的，我們希望利用這個新元素，可以幫助解決問題的靈活性和增力解決問題的方法，藉此令新的模糊 Petri 網可以解決以往不可解決的問題。
在現有的模糊 Petri 網的推理過程中，每一條規則都會有一個固定的可能性數值，無論所需的環境變數是怎樣，這個可能性數值都是不變固定的。不過，這個數值絕對是一個影響推理結果的重要因素，所以我們本著這個範疇去嘗試改進這個可能性數值成爲動態的可行性。
在整個研究的過程中，我們發現現有的模糊 Petri 網其實並不能完全應用於中國醫學上，所以我們亦希望透過這個創新的概念而可以將傳統的中國醫學應用到現今的先進科技。

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Contents

List of Figures

Chapter 1

Introduction

In today's world, as we all know that there would be more and more information, and thus different kinds of the knowledge would then be introduced or accumulated. Nowadays, most of the system is specific to a particular kind of knowledge, which is not general for all purpose. As a result, more supporting functions on the modelling can further be developed to improve and aim at an effective and efficient way on various kinds of technique. Therefore, if we can introduce some methodology to solve the problem in general, this can give significate contribution to knowledge-based system or other expert system.

Chinese Acupuncture

Hong Kong people always suffer from various kinds of sickness and they are willing to try different ways to solve their health problem, not just only depend on the Western medicine. With the legalization on Chinese medicine in Hong Kong, for example, authorized universities offer appropriate advanced and certified course in order to provide systemical knowledge to new learners on Chinese medicine. At the same time, current Chinese doctors need to get licenses and certified by Hong Kong government. These regulations could give the society more confidence and convenience in seeking Chinese medicine treatment. To promote Chinese medicine, more resources are needed and then they should be made available to the public.

The idea of computerization applied to the Chinese medicine would be the trend of the future research direction or even the commercial direction. Since there are a lot of unstructured and not well organized information on the Chinese Medicine, however there is not much developed system about Chinese Medicine. With these reasons, a pre-processed data, real-time and interactive computer graphical system could help people to understand more about Chinese Medicine. Such knowledge-based visualization applications can enhance the learning interest through studying knowledge based on different approaches, repeatable revision of a particular topic and even personalized learning by the user. With the user-friendly interface, more students and professionals would have greater interest in the study and research of the Chinese Medicine.

Throughout Chinese history, both acupuncture theory and practice has steadily evolved offering many effective treatments. Acupuncture did not interact with modern Western medicine until recent years when China ended a period of isolation and resumed foreign political and cultural communications. The primary reason for the slow acceptance of acupuncture is its diagnosis approach that there is no substantial, scientific reality behind, since it is a non-demonstrable mechanism. Therefore, it is worth to integrate the Chinese medical knowledge into the current IT technology.

Obviously, a good visualization system would help in presenting such abstract knowledge in order to be more "readable". With such kind of applications, Western doctors can learn more about the knowledge about Chinese Medicine, and understand the reasons behind the diagnosis . This would improve the communication between

Chinese and Western doctors on the research of medical knowledge based on different approach on diagnosis methodologies.

Artificial Intelligent

There are previous works on graphics system using artificial intelligent technique and approaches [1, 2]. Surely, there are many artificial intelligent approaches such as Self-Organizing Map (SOM), Neural Network (NN), Fuzzy Logic, Expert System etc. All of them can improve the functionality, efficiency and it can also provide user-friendly interface to the system users.

In our real world, knowledge usually has been classified and pre-processed before application, some of them could be represented using fuzzy concepts since human cannot always give the explicit description about their perceptions. As a result, a fuzzy logic approach could adapt the unclear message from user description or user basic knowledge. Even little information is given, we can then extract the useful information as much as possible in order to search and present the best relation.

Knowledge in expert systems [3] is updated or modified frequently, expert systems may be regarded as dynamic systems. Suitable models for them should be adaptable. That is, the models must have ability to adjust themselves according to the changes of systems. Nevertheless, the lack of learning algorithm [4] in Fuzzy Petri Nets (FPNs) can not deal with the potential changes of actual systems.

In current stage, there still exist two major problems in the development of fuzzy systems. The first one is the difficulty in handling fuzzy sets which do not have a clearly defined base. The other one is the difficulty in acquiring and fine-tuning the knowledge representation parameters in the fuzzy system model. Many similarity-based fuzzy reasoning methods have been proposed.

In fact, the main contribution and the ordinary approach of fuzzy logic is to incorporate the new idea into problem-solving systems.

1.1 Current Problem

In the traditional FPN model, each transition has **one constant certainty value.** This constant certainty value is assigned a value between 0 to 1 when the transition is built. In the original rule reasoning methodology, this certainty value is always constant and would not be updated for any cases. Moreover, in reality, the concept of certainty value should be modified or corrected according to various environmental status.

Let us consider how human reacts on various matters. If there are several ways to finish/reach the target, we would find the best way. The best way means a possible way to reach the nearest target. The first criterion obviously is the similarity between the model result and the actual result. While the second criterion is the probability of the transition to be fired/ocurred.

The problem of the traditional model is that a constant certainty value is used during the whole reasoning process. The traditional FPN only considers the relationship between the fuzzy value of resultant place and the fuzzy value of the starting places. It ignores the relationship between the starting places and the properties of the transition (e.g. certainty value). As a result, even the traditional FPN model can be used on lots of the problems, it still cannot model some special cases.

Besides, we found that the traditional reasoning process has some limitations. In the old model, when there is one unfired transition, all the past information would be lost. The system would not remember the status of the transition. Although the information of the antecedent places could still give contribution to other transitions, the status of those fired transitions could not give any extra message to the system in reasoning. If we can remember this kind of information which was considered to be useless, the influence results would be better.

In most of the rule based systems, the aim is usually to get a correct goal only. While whole system architecture is comparatively neglected, this leads to the efficiency problem and also the problem of confidence. The current model mostly is developed from the **bottom-up** design approach. In every expert system project development, we have to first define the rules to be obeyed. Such rules are usually consulted by the human experts. However, human experts solve problems not only just based on their professional knowledge, but also with the environment status and other information. They act as intermediate facilitators to give the best, or most balancing, solution.

In the following example, we would like to show the importance of the "deterministic criteria" could be adapted with the current problem, but not for general cases even using the same knowledge base. For example, when the investors consult a stock analyst expert about their investment strategy, the analyst expert has to collect a lot of information, including from the investor, from the current investment atmosphere, and also from the behavior of other investors. With all these information, the expert has to classify which information are important to this "specific" investor. Let's say, if the investor **A** has more knowledge and experiences on stock market, his portfolio may invest more in stock market. While another investor **B**, who is a beginner in stock market, then his portfolio should invest less in stock market.

1.2 Research Proposal

With the brief current status described in the above section, we therefore have the idea to develop a system to deal with this problem. As mentioned, Chinese medicine is not well-documented and not well-organized in most of the teaching materials. Besides, the current teaching materials are usually in the form of words, instead of some kind of visual aids. As a result, the suggested proposal can be used as an auxiliary reference during the teaching or learning purpose.

As shown in Figure 1.1, the system has several components: (a) core expert system which is responsible for inferencing; (b) Chinese medicine knowledge which is the supporting background information to the expert system; and (c) 3-D human data which is used for 3-D visualization.

From the diagram, the system would support the user inputs which allow system users to give their personal preferences, such as which part of body is of interest, which kind of knowledge is concerned, or even the level of details.

Here is the diagram of the system architecture:

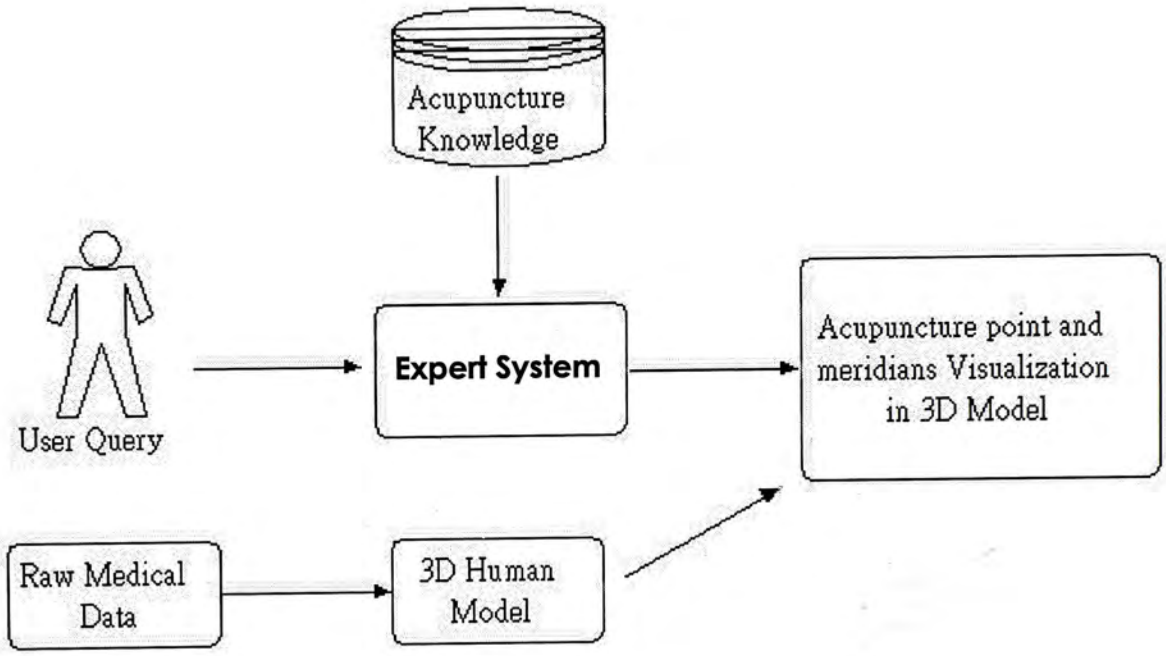

Figure 1.1: Suggested Expert System

The expert system would use the Chinese medicine knowledge as the core background information. A virtual human is constructed using the 3-dimensional raw data, and is also tailor-made for easier manipulation in this system. Whereas, in aspect from Chinese acupuncture knowledge, they focus on the skin texture rather than the internal organs and structures to determine illnesses and make decisions. As a result, the system would be quite different from the currently used western medical applications. Hence, our proposed research would then target an Chinese medicine and desire to discover some special characteristics and features.

1.3 Research Target

This research project basically has two major targets.

The primary motivation for this research is to *give good organization for the Chinese medical knowledge.* In most of the current Chinese medicine materials, the knowledge is usually described by words and words only without clear descriptions and essential details. As a result, many students have to learn from experience in order to verify those knowledge stated on the book or other reference materials. Obviously, this is not a scientific way of learning nowadays. Therefore, if we can present these knowledge in a systematic manner, it can then improve the learning style and the learning time on Chinese medicine knowledge.

In recent years, the biochemistry technology is a hot topic in various sectors. People now have much concern on their body health, especially in those well-developed countries. Many scholars and researchers believe the development of biochemistry technology is a new trend in the coming decade. In the past two decades, many useful and powerful softwares and hardware have been developed. This new trend could use these systems, incorporate with other knowledge to enhance and improve the current research process time. Its efficiency can help to analyze the complex model of our human body and the DNA structure.

The second motivation is *the evolution of the fuzzy petri net modelling and its reasoning algorithm.* Since the knowledge of Chinese medicine has never been fully systemized and it is not well presented, it is worth to incorporate the knowledge into the approach in Computer Science. Besides, the approach in Chinese medicine is totally different from that in Western medicine, so we would like to work on introducing some new component in the traditional fuzzy petri net model in order to fit for application in Chinese medicine.

Although current fuzzy petri net models can already solve most of the problems, we target to improve its efficiency and accuracy. The current theory has been undergone an evolution, or we can say modification. In the research area in artificial intelligence, most researchers focus on the improvement of the training algorithm, reasoning influence and the fuzzy set interpretation. During the literature review period, we discovered that there is potential fundamental research value in modeling.

Finally, we hope that this research can help future research on the area of fuzzy petri net and give the future researchers a starting point on further modification of *dynamic certainty factor*. Besides, we hope that this research could give stimulation to interested researchers to improve the traditional FPN model so that more complex problems can be solved using AI techniques or approaches.

1.4 Thesis Overview

Chapter 2 is a brief introduction of the Fuzzy Logic. We would describe the fuzzy set definition, their operations and the representations. The fuzzy logic is a fundamental approach to model our stochastic world. Besides, this chapter would describe about the fuzzy petri net model and its reasoning algorithm. Lastly, we would also present some well-known application using this concept.

Chapter 3 would describe the definition of the new component - dynamic certainty factor and the new reasoning methodology. Several examples are given to illustrate how this new model can represent some special problems, such as acupuncture knowledge.

Chapter 4 would give more examples to illustrate the feasibility of our new FPN model. The Chinese acupuncture knowledge has been chosen to integrate with this theory. The feasibility of the new approach on FPN model and its reasoning algorithm has been shown in this research work.

Finally, Chapter 5 gives a summary of this research work and some suggestions on the future research.

Chapter 2

Fuzzy Logic and Fuzzy Petri Net

The foundation of fuzzy set theory is introduced by Lotfi Zadeh in 1965. There are many continuous important research applying his fuzzy theory on real-life problems. Zadeh fuzzifies a variety of mathematical structures to provide more appropriate models of the use in the process of reasoning with vague data.

With the introduction of fuzzy set theory, many other derivatives have also been developed. At the same time, researchers try to incorporate it with other AI theory [5]. In the past AI, every fact only has either true or false value - concept of binary value which is a discrete interpretation. It is a state-of-art research on fuzzy set theory, because Zadeh extended the binary world to a infinite and continuous interpretation for knowledge representation. This evolution enhances the original binary interpretation and gives more flexibility to the reasoning result. The famous applications include fuzzy cleaning machine, fuzzy cooker and even some fuzzy logic equipped electronic appliances such as hand-held video camera etc.

A Fuzzy Petri Net (FPN) formalism [6] is a derivative of Petri Net (PN) which has been demonstrated to be a powerful modelling formalism [7]. In fact, modelling a system using PNs has many advantages compared to other modelling schemes. The graphic representation of PNs makes the models relatively simple and easily understandable.

Petri Nets (PN) models and net theory have become an important computational paradigm to represent and analyze a broad class of systems. As a computational paradigm for intelligent systems, net theory provides a graphical language to visualize, communicate and interpret engineering problems, as well as a specification and engineering language which can be used as a development, simulation and implementation tool. PN have the ability to represent and analyze in an easy way concurrently and synchronization phenomena, like concurrent evolutions. Furthermore, PN approach can be easily combined with other techniques and theories such as object-oriented programming, fuzzy sets, and neural networks. These combined PN are widely used in computer systems, manufacturing systems, robotic systems, knowledge-based systems, process control, as well as other kinds of engineering applications.

Some types of FPNs have been proposed to handle problems in different applications. A FPN model can be used to represent the fuzzy production rules (each rule describes the fuzzy relation between two propositions) of a rule-based system. Based on the tailor-made FPN model, a FPN algorithm has been proposed to perform fuzzy reasoning automatically. There would be other extension on fundamental PN, a fuzzy neural Petri net has been proposed for representing a fuzzy knowledge base and for fuzzy reasoning [8]. Also, many FPN techniques have been widely used for modelling and analyzing in various area, including both commercial and research applications.

2.1 Background

Fuzzy logic approach to modelling or representation has been proven to be a successful methodology. Human linguistics is inevitably vague, such as "I am stupid", "Time goes very fast", "Today is blue" etc. All of these statements cannot give a clear and define information to other people. Unlike some format statements such as "11 is a prime number", "4 is odd number" etc, these statements could give an absolute information (either true or false). The main difference of the empirical statement ("I am smart") from the formal statement is the degree of truth in the empirical statement.

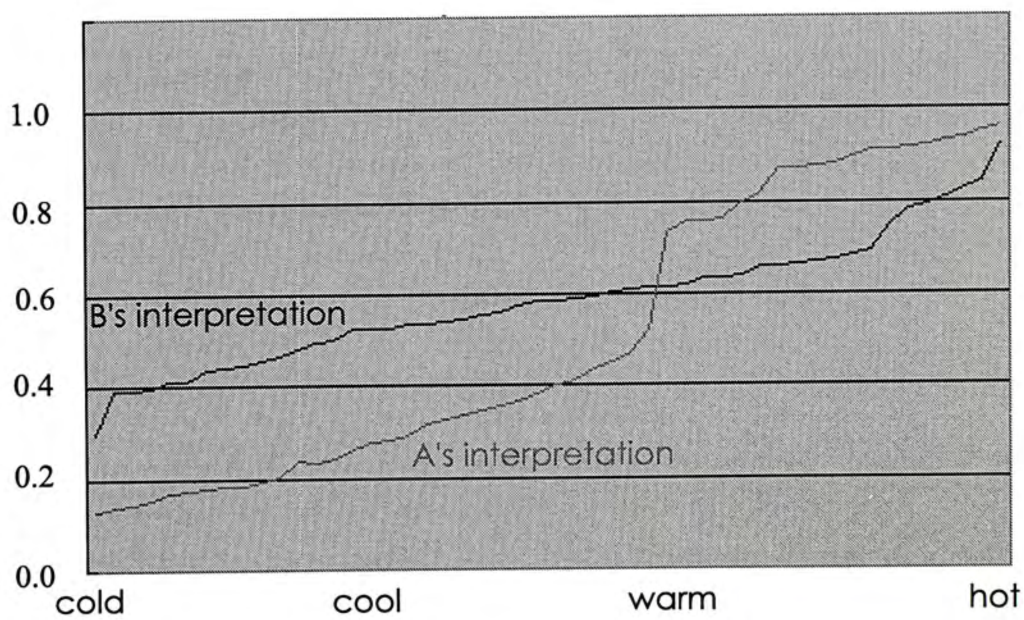

Figure 2.1: Interpretation of the same linguistic word

Now, we can differentiate the idea between the fuzzy modelling and the true-false modelling. Nevertheless, the interpretation of a fuzzy terminology is also a problem. Even people use the same linguistic word, each one would have more or less different interpretation of the same word/phrase. This problem is really hard to solve. Since this is not a technical problem, we can just try to compromise most of the users's opinions, that is called the standard **scaling interpretation.**

In Figure 2.1, it shows a simple example of different interpretation of the same "feeling" concept. From the figure, say the example word "cool", **A** would transform this word to the numeric number as 0.28, while **B** would give the value as 0.5. Such kind of differences is due to different tolerance of human. Besides, there is a sharp change of **A**'s interpretation. The entire trend of variations between A and B is totally difference. Therefore, the **scaling interpretation** of A should be used independently from that of B.

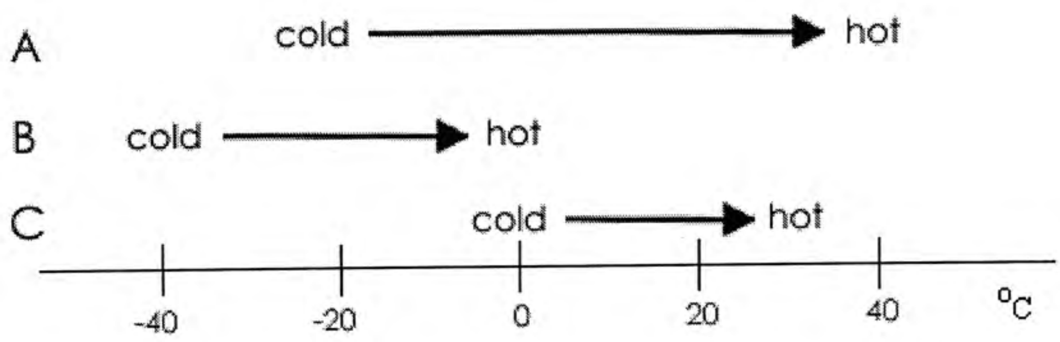

Figure 2.2: Different scaling on linguistic word

Another example can be showed in Figure 2.2. From the figure, each people would have their own scale on interrelating the "temperature". As shown, even for the same temperature, say 0 °C, **A** would feel *warm*, **B** would feel *hot*, and **C** feel *cold*. In this example, it is easy to illustrate there is no an absolute objective scaling on a linguistic word. Besides, their range of the same "temperature interpretation" are different too.

The range of **A** is from *-20 to 35* (55) , **B** is from *-40 to -5* (35), and **C** is from *0 to 25* (25). Nevertheless, in our current fuzzy model, we usually use the **same** range [0,1] to deal with all such transformation from a linguistic idea to a numeric representation.

So far, we have described briefly the basic concept of the fuzzy concept. Such fuzzy concept is mainly used to handle problems in our complex world. Though the domain of the complex world and the mathematical knowledge are totally different, and fuzzy logic cannot fully handle **all** possibilities in real cases, but it is still a meaningful research project.

2.2 Fuzzy sets

Definition 1 *Given a set X and a subset $A \subseteq X$, the characteristic function*

$$\chi_A : X \to \{0,1\}, \quad x \mapsto \begin{cases} 1 & \text{if} \quad x \in A \\ 0 & \text{otherwise} \end{cases} \tag{2.1}$$

Fuzzy set theory generalizes the concept of set membership by extending the range of the characteristic function from the set {0,1} to the interval [0,1]. This concept evolves from the binary set {0,1} to the infinite set [0,1]. Since the domain of the set now extends to infinity, we can define different levels of preciseness to fit with the particular problems. That means, a more complex fuzzy set can also be represented by [0,1] with more precision. If fuzzy set theory is not used, we have to define a large set (with large number of fuzzy elements) to represent the complex problem for the cases. In this way, the algorithm can then be speeded up by using a better representation modelling.

Definition 2 *Given a set X, a fuzzy subset A of X is a function*

$$\mu_A : X \to [0,1] \tag{2.2}$$

For an $x \in X, \mu_A(x)$ is called the **membership value** or **grade of membership** of x in A

To understand more about fuzzy set concept, let us use an example to illustrate the above definition:

Example. Let $\mathbf{S}$ be the set of all real numbers, and let

$S_f = \{s \in \ \mathbf{S} \ | s \text{ is positive and large}\}$.

This subset, S_f, is not well-defined in the classical set theory. Although the statement "s is positive" is precise, the statement "s is large" is vague. However, now we has introduced the idea of membership function. This subset then becomes a reasonable and meaningful statement. If the membership function is defined as:

$$\mu_{S_f}(s) = \begin{cases} 0 & \text{if} \quad s \leq 0 \\ 1 - e^{-s} & \text{if} \quad s > 0 \end{cases}$$

then the fuzzy subset S_f, associated with this membership function $\mu_{S_f}(s)$, is well-defined. In this way, for any real number s would have a degree of truth value $\mu_{S_f}(s)$ which can indicate this real number s whether is a positive large number or not.

Membership function can be defined in various form, depending on the specific problem sets.

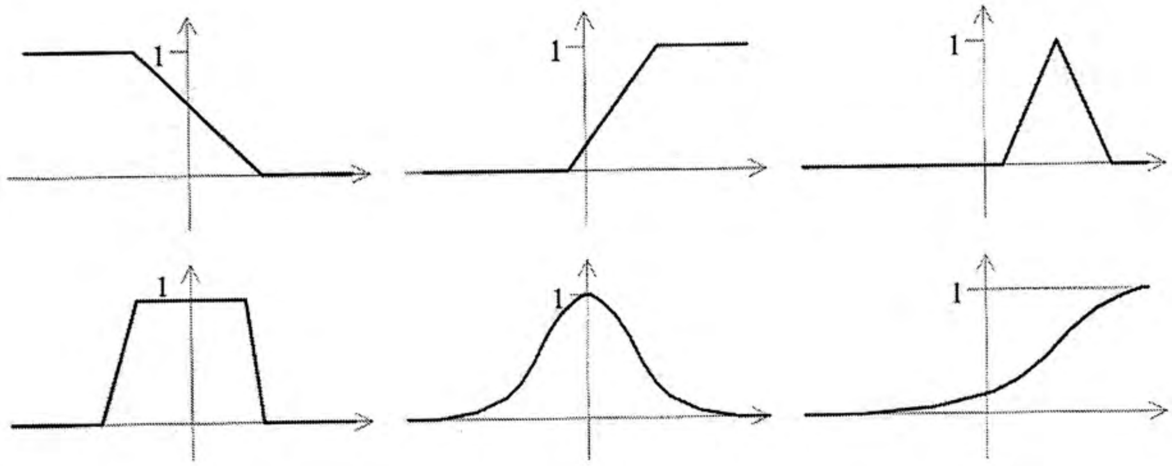

Figure 2.3: Various shapes of commonly used membership functions

Definition 3 *Given a set X and two fuzzy sets $A, B \in F(X)$, A is called a subset of $B(A \subseteq B)$ iff*

$$\forall x \in X : \mu_A(x) \leq \mu_B(x) \tag{2.3}$$

Triangular form is one of the commonly used and simplest membership function. The definition is given as follows:

Definition 4 *Given three numbers $a, b, c \in \mathbf{R}$ with $a \leq b \leq c$, the* ***triangular fuzzy number*** *defined by a,b and c, denoted as $\mu_{tri(a,b,c)}(x)$ with*

$$\mu_{tri(a,b,c)}(x) = \begin{cases} 0 & \text{if} \quad x < a \\ \frac{x-a}{b-a} & \text{if} \quad a < x < b \\ 1 & \text{if} \quad x = b \\ \frac{x-c}{b-c} & \text{if} \quad b < x < c \\ 0 & \text{if} \quad c < x \end{cases} \tag{2.4}$$

It is easy to see that a triangular fuzzy member as defined above is normal and convex and the case $x = b$ is the only point where the membership grade of this fuzzy number is the maximum, 1.

2.3 Operations on fuzzy sets

There are some basic operations in set theory, crisp and also the fuzzy set theory. Zadeh defined the operations: *intersection, union*, and *complement* as follow:

$$\begin{aligned} \mu_{A \cap B}(x) &= \min[\mu_A(x), \mu_B(x)] \\ \mu_{A \cup B}(x) &= \max[\mu_A(x), \mu_B(x)] \\ \mu_{\overline{A}}(x) &= 1 - \mu_A(x) \end{aligned} \tag{2.5}$$

Applied to the characteristic functions of ordinary sets, the above definitions hold in fuzzy sets. They also satisfy most of the axioms of ordinary set theory, e.g. they are associative, commutative, and mutually distributive.

These are not the only definitions that extend ordinary set operations. In general a binary operation op on two fuzzy sets over X is a function $op : F(X) \times$

$F(X) \rightarrow F(X)$. In current fuzzy set theory, most $F(X) \in [0,1]$ for easy operations.

The above defined operations are very useful in fuzzy reasoning. During the fuzzy reasoning process, it is common to deal with several fuzzy sets to determine the result value of another fuzzy set.

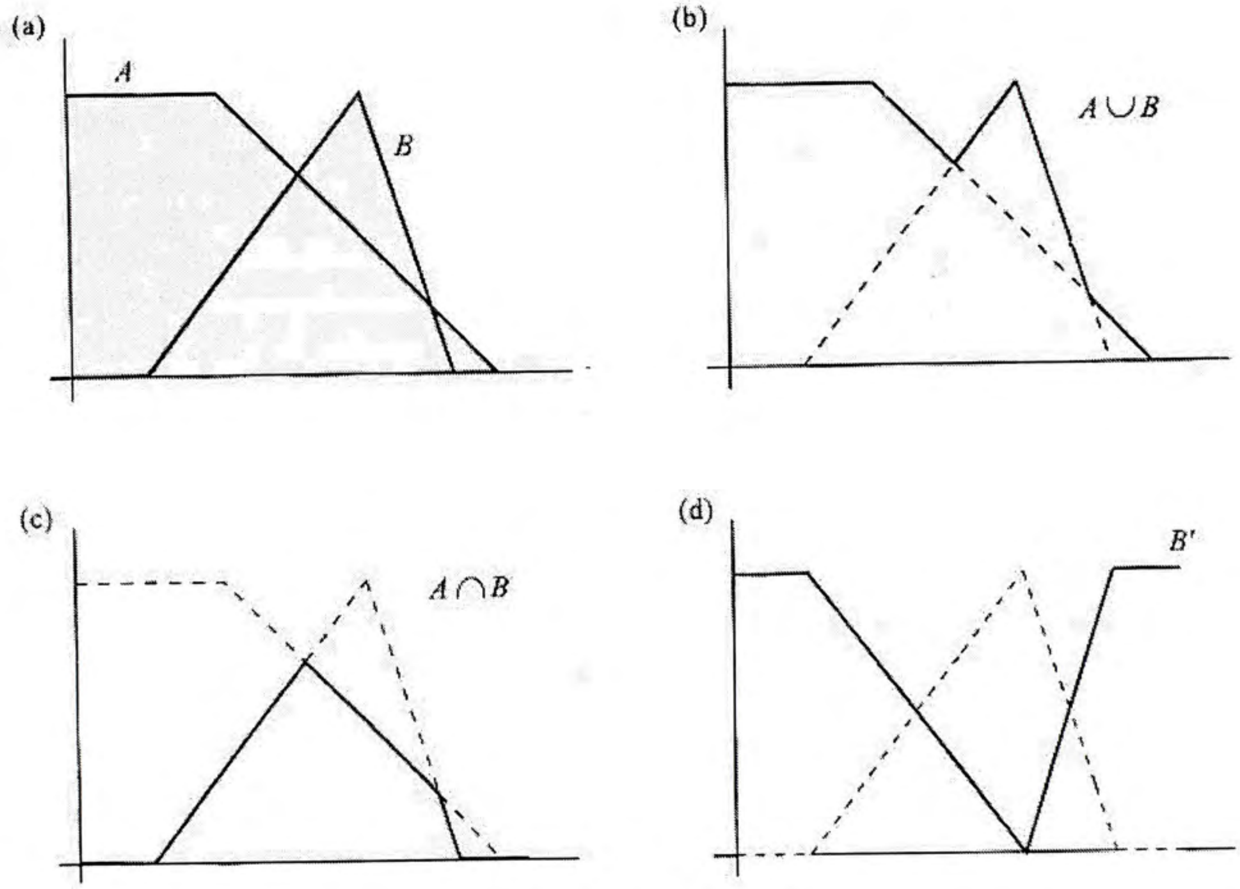

Figure 2.4: Operations on fuzzy subsets

(a) Membership functions of the fuzzy subsets A and B. (b) Membership function of their union; (c) of their intersection; and (d) of the complement of B.

2.4 Fuzzy logic

Fuzzy logic could be viewed as a generalization of multi-valued logic that it provides a wider range of tools for handling with *uncertainty* and *imprecision* in knowledge representation, inference, and decision analysis.

Fuzzy logic is logic; its ultimate goal is to provide foundations for approximate reasoning using imprecise propositions based on fuzzy set theory.

Generally, **fuzzy logic** provides several useful features :

- usage of *quantifiers*, such as 'most', 'few', 'many',etc ;
- usage of *probabilities*, such as 'likely', 'unlikely',etc ;
- usage of *possibilities*, such as 'possible', 'impossible',etc ;
- usage of *truth-values*, such as 'true', 'not true', etc ;
- usage of *predicate modifiers*, such as 'very', 'quite', etc ;

Many readers may find the "min-max" principle in fuzzy logic disturbing. That is, they find it difficult to accept

$$T(A \wedge B) = \min[T(A), T(B)]$$

and

$$T(A \vee B) = \max[T(A), T(B)]$$

Surely, we do not believe that fuzzy logic is adequate to describe the complex world we are living in. However, it would be already an improvement of the two-valued logic in inference process, at least it gives us a way to handle fuzzy information.

When we use fuzzy logic, we can set a threshold of the reliability of the information. For example, we may require that every clause has truth-value at least equal to 0.99. If so, a clause has to be "very true" in order to continue the inference process. Instead, if we lower the threshold, say to 0.75, we then would allow more *less reliable* (more or less true) information. However, the advantage is more solutions are available. In another words, there is a trade-off between the number of solutions and the reliability of these solutions.

Example

This example would be illustrated by both classical theory and fuzzy logic theory.

$$(\overline{b} \wedge (a \Rightarrow b)) \Rightarrow \overline{a}$$

Premise	Peter cannot work
Implication	If Peter is young then he can work
Conclusion	Peter is not young

This example does not make much sense in our linguistic understanding. The premise "Peter cannot work" would not directly deduce the conclusion "Peter is not young" in our normal thinking. This is the one limitation of the two-valued logic in applications. It is because two-valued logic can only describe "young or old", "can or cannot", etc.. When the reasoning rule is the kind of "backward" direction, it could induce such kind of problem. In another point of view, the same rule is used but with fuzzy logic approach:

Premise	Peter cannot work much
Implication	If Peter is much young then he can work more
Conclusion	Peter is not so young

With the use of fuzzy logic, the above example becomes a more reasonable inference. In such examples, one only needs to select/match reasonable membership functions to describe "young, very young, old, very old, much , much more, hard, very hard", etc., as a result, they can be meaningful and practical for the applications in considerations. In fuzzy logic, the premise could be slightly different from the implications. You can refer to the above example, the keyword of the premise "work much" is not exactly the same as the that in the implication "work more". This *threshold* on matching the rules allows the fuzziness and thus results a flexibility in deduction of the conclusion. That is the "back box" reason for such examples to become more reasoning and meaningful in linguistic inferencing.

Application

After the introduction of fuzzy logic concept, there are many applications using fuzzy logic, famous medical applications such as CADIAG-1, CADIAG-2 system [9, 10, 11, 12] have improved the quality of human life . These systems aim to introduce the simulation of generating the membership value from facts by observations. Moreover, it shows the evidences on rule inferencing are feasible.

The fundamental idea in this research area includes: (a) usage of a mathematical description of the system and (b) a method for solving the equations arising in part (a) in *real time*. The second condition is crucial, because it can help the controller to make decision, and take appropriate action to avoid a collision. This work can be considered as the implementation of a simple idea: automating the decision making of a human expert to control a process.

2.5 Weighted Fuzzy Petri Net

The fuzzy petri net (FPN) is introduced by Chen et al [13, 14, 8]. which can deal with fuzzy production rules. During a series of research development, this FPN model is enhanced with the including of a set of threshold values and weights, this model is named as Weighted Fuzzy Petri Net (WFPN). Formally, this WFPN is a form of tuple:

$$WFPN = (P, T, D, Th, I, O, F, W, f, \alpha, \beta, \gamma, \theta)$$

where

$P = \{p_1, \ldots, p_n\}$ is a finite set of places;

$T = \{t_1, \ldots, t_m\}$ is a finite set of transitions;

$D = \{d_1, \ldots, d_n\}$ is a finite set of propositions;

$Th = \{\lambda_1, \ldots, \lambda_2\}$ is a sets of threshold values;

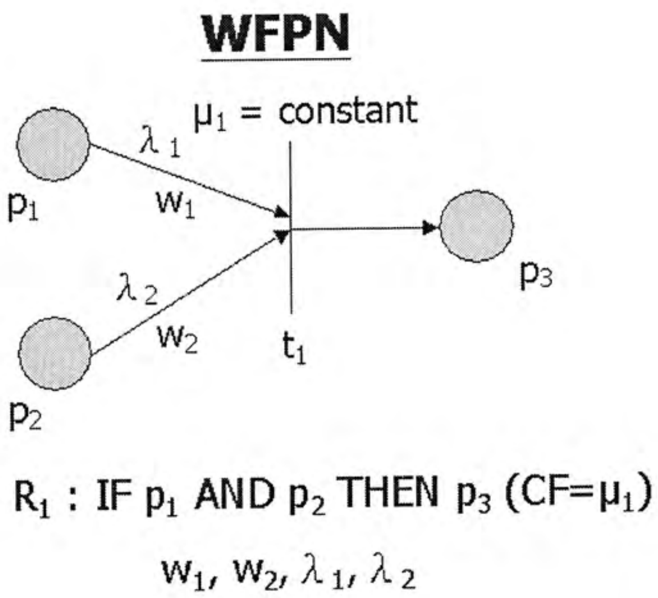

Figure 2.5: Weighted Fuzzy Petri Net

I is an input mapping from T to P ($I : T \to P$)

O is an output mapping from T to P ($O : T \to P$)

$F = \{f_1, \dots, f_r\}$ is a set of fuzzy sets;

$W = \{w_1, \dots, w_p\}$ is a set of weights of WFPN;

f is an association mapping which assigns a certainty value

to each transition ($f : T \to [0, 1]$)

α is an association mapping ($\alpha : P \to [0, 1]$)

β is an mapping function ($\beta : P \to D$)

γ is an association mapping from places to threshold values ($\gamma : P \to Th$)

θ is an association mapping from places to weights ($\theta : P \to W$)

2.6 Fuzzy reasoning

A detailed interpretation of the places and transitions is application-dependent. For instance, in two-valued logic (true-false logic), a transition is interpreted as a rule (that detailedly describe the conditions and conclusions), input places are treated as conditions, whereas the corresponding output places represent conclusions. The rule (statement/conclusion) becomes activated when its conditions are satisfied. Being more specific, the transition fires (rule is valid).

If (PRESENT CONDITIONS), then (ACTION TO BE TAKEN).

Fuzzy Logic Rule Reasoning Algorithm

In fuzzy logic rules, they are usually in the form of $a \Rightarrow b$. For fuzzy logic performed on a fuzzy subset A, we have a membership function μ_A describing the truth values of $a \in A$ and $b \in A$. This form $a \Rightarrow b$ can be interpreted, in linguistic terms, as

"(IF $a \in A$ is true with a truth value $\mu_A(a)$ THEN $b \in A$ is true with a truth value $\mu_A(b)$) has a truth value $\mu_A(a \Rightarrow b)$"

From the above definition, we can observe the fact that we only handle the "degree of truth" values during the fuzzy logic rule reasoning, instead of the "element" values of the propositions. This is the crucial point on fuzzy logic reasoning. You can benefit from the normalization of different fuzzy membership to a standardized term - "degree of truth". During the manipulation of the fuzzy model, we just need to focus on the relationship of the "degree of truth" between the fuzzy membership terms.

Algorithm

$$
\begin{aligned}
\text{Let } w_{max} &= \max[w_1, w_2, \ldots, w_n] \\
RS_{max} &= \alpha(P_i) \text{ of } w_{max} \\
RS_{all} &= \min[RS_1 + (RS_1 - RS_{max}) * (w_{max} - w_1)/w_{max}, \\
&\quad RS_2 + (RS_2 - RS_{max}) * (w_{max} - w_2)/w_{max}, \\
&\quad \ldots \\
&\quad RS_n + (RS_n - RS_{max}) * (w_{max} - w_n)/w_{max}]
\end{aligned}
$$

The degree of truth of the consequence $= RS_{all} * CF_i$

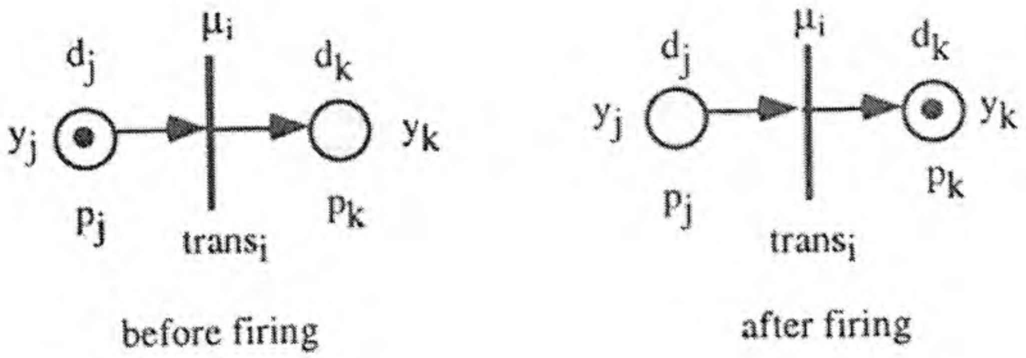

Figure 2.6: State transition firing process

Figure 2.6 is a simple example of fuzzy petri net firing during a system reasoning. The example consists of 2 places and 1 transition.

Suppose we have the fuzzy rule base :

1. "IF x is positive small THEN y is negative small."

2. "IF x is positive medium THEN y is negative medium."

3. "IF x is positive large THEN y is negative large."

Using the fuzzy logic notation with the definition of an appropriate membership value μ, we can rewrite the above three implication statements as follows:

1. "IF x is PS THEN y is NS."

2. "IF x is PM THEN y is NM."

3. "IF x is PL THEN y is NL."

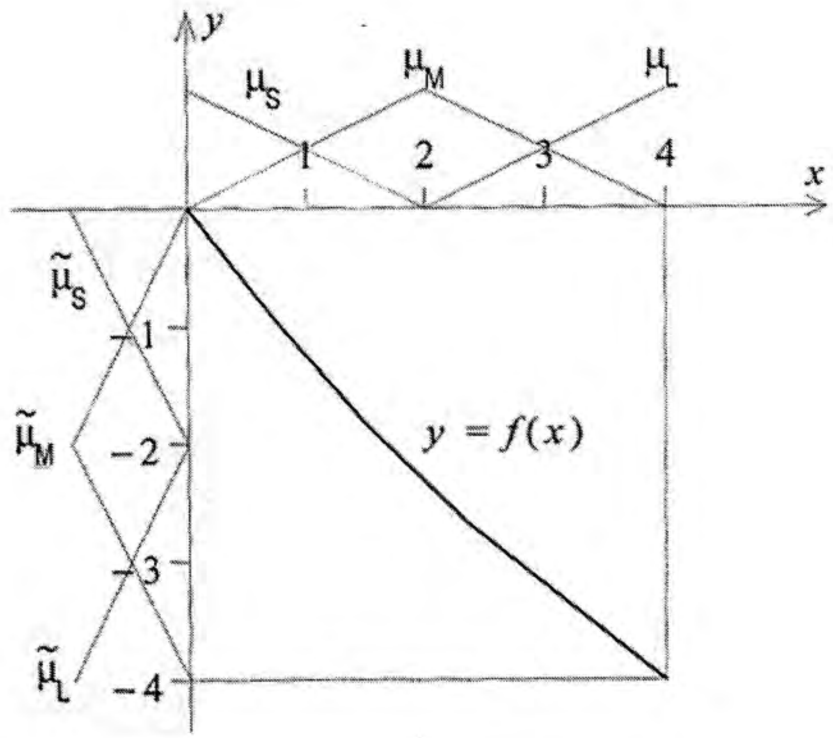

Figure 2.7: An example using a fuzzy rule base

Comparing to the classical two-valued logic inference, only one rule is needed in fuzzy logic inference instead of three in this example. It is because we can combine the fuzzy factors "small", "medium" and "large" into one fuzzy membership function for evaluation. Moreover, with the definition of the relation between x and y. In this example, x and y has a direct proportional relationship as shown in Figure 2.7.

Incorporate with the fuzzy membership function, the fuzzy membership function μ can now infinitely tell us many different truth values for the statement "x is small".

Reasoning steps

1. find out the input states
2. determine the truth value of inputs based on the defined membership functions
3. process the reasoning algorithm
4. calculate the truth value of outputs with the defined relationship model

Example on reasoning

Using the same membership functions as the above example, we now have the initial state "$x = 1.5$". By the membership μ_s (evaluate for the term "small"),

1. $x = 1.5$
2. $\mu_s(x) = 0.75$, indicate x is quite positive small.
3. $y = f(x) = -0.75$
4. $\widetilde{\mu_s}(y) = 0.75$

5. conclusion: "y is negative small."

We can observe that there are more steps on fuzzy logic reasoning, and surely more complex rule systems would have more steps in order to maintain the correctness and understandable algorithm.

2.7 More about fuzzy logic

Adaptive Fuzzy Control

Adaptive control is a method of designing a controller with some adjustable parameters and an embedded mechanism for adjusting those parameters. For each control cycle, the adaptive algorithm is normally implemented in three basic steps:

1. collect observable data to calculate the controller's performance
2. calculate the adjustments to a set of controller parameters
3. parameters are adjusted to improve the performance in next cycle

Traditionally, there are four fundamental approaches for adaptive control:

1. gain scheduling
2. model reference adaptive system
3. self-tuning regulator
4. dual control

Adaptive fuzzy control is widely used, since it can be used in various controlling systems [15, 16] and fuzzy modelling systems.

Health Monitoring Fuzzy Diagnostic System

Most current health monitoring systems usually check the human body's temperature, blood pressure, and heart rate. These data would then be compared with the defined individual upper and lower limits. Such monitoring system would give the alert signal when there is any one of the conditions moves out of the pre-defined range. This signal would be aware and doctors can then examine the patient, and further give a proper diagnosis in order to release the patient's problem.

It is not difficult to convert the current simple system to a fuzzy logic based system. There are three core conditions: i) body temperature, ii) blood pressure, and iii) heart rate. Indeed, each individual symptom can reflect different illness.

Here are some possible cases:

1. high body temperature indicates high fever associated with the body fighting against infectious virus or bacteria

2. high blood pressure would associate with some kidney disease, hormonal disorder

3. low heart rate indicates the blockage between pacemaker and atria

Not only the individual symptoms can give us information, their combinations could also give us other information, which is not described in the individuals. For example, low blood pressure and high body temperature might say a serious exposure to heat. If we define the fuzzy membership function of the three conditions, each of them has three setting values (normal, high, low), there would have totally 27 different possible cases, and thus at most 27 illness.

2.8 Chapter Summary

We have described the fundamental definition of a classical fuzzy concept in this chapter. In Section 2.1, some background information of fuzzy concept has been described briefly. The state-of-the-art fuzzy set has been briefly explained in Section 2.2. The classic fuzzy operations in Section 2.3. Fuzzy logic is briefly introduced in Section 2.4. Fuzzy rule model and its reasoning methodology in Section 2.5 and Section 2.6. Finally, more research on fuzzy logic is also described in Section 2.7.

Recapitulating, more complex, higher-level, and rule-based structures applied to model approximate reasoning by using fuzzy logic and fuzzy petri net since it is introduced.

There are a significant number of fuzzy set based generalizations of Petri nets [17, 18, 19]. Most of the modifications or approaches concentrate on modelling the mechanisms of approximate reasoning and are largely preoccupied by a suitable handling of the **if-then** statements. The primary motivation of these attempts is in a proper representation of the semantics of the underlying reasoning mechanisms.

Chapter 3

Dynamic Certainty Factor

3.1 Definition

With the introduction of the new component to the current FPN model, we define the new FPN model as follows:

$$newFPN = \{P, T, D, I, O, F, f, \alpha, \beta, \gamma, \theta, Th, W, W'\} \tag{3.1}$$

$P = \{p_1, p_2, \ldots, p_n\}$ denotes a set of places

$T = \{t_1, t_2, \ldots, t_n\}$ denotes a set of transitions

$D = \{d_1, d_2, \ldots, d_n\}$ denotes a set of propositions

$I(O)$ is the input(output) function, a mapping from transitions to places

$F = \{f_1, \ldots, f_r\}$ is a set of fuzzy sets

$f : T \rightarrow [0, 1]$ is an association function, assigns a certainty value to each transition

$\alpha : P \rightarrow [0, 1]$ is a mapping function from places to real values between zero and one

$\beta : P \rightarrow D$ is a mapping function from places to propositions

$Th : P \rightarrow [0,1]$ is a function which assigns a threshold value to each placep_i

$$Th = \{\lambda_1, \lambda_2, \ldots, \lambda_m\}$$

$W : P \rightarrow [-1,1]$ which assigns the input weights of each rule

$\gamma : \alpha, W \rightarrow [0,1]$ which is a mapping function for the certainty factor

$W' : P \rightarrow [-1,1]$ which is the set of weighting of each place for certainty calculation

θ is an association mapping from places to weights ($\theta : P \rightarrow W$)

3.1.1 Background

The motivation of introducing such new component *dynamic certainty* into the traditional model, is simply because we would model as close to nature human thinking as possible [20]. The function $\gamma(\alpha, W')$ can be tailor-made for different kinds of problem. Either linear or non-linear function can also be used. Since we would like to model the certainty value as the function of antecedents, it is generally that this function is an increasing and continuous function in the range [0,1]. However, the function need not to be one-to-one mapping function. Since the different combinations between the antecedents could return a different result, it could be many-to-one function. In this way, forward chaining technique could be used to incorporate in this new model in the rule reasoning [21].

In real world, it is nature that when the facts (antecedents) happen with higher certainty, that is with higher fuzzy value, the deduction (consequence) would have higher certainty. Though the fuzzy value can be used to represent this reasoning effect, nevertheless, when we need to determine the best reasoning in the entire knowledge system, the certainty of each rule is the same for all fuzzy values in each case. In the traditional petri net model, if the same set of rules are fired, the best reasoning path is deterministic. It would not encounter the fuzzy value of the antecedents. However, this set of fuzzy values would be very useful in rule reasoning. It is because they are the characters of each problem, and the best reasoning would not only be determined by the system model.

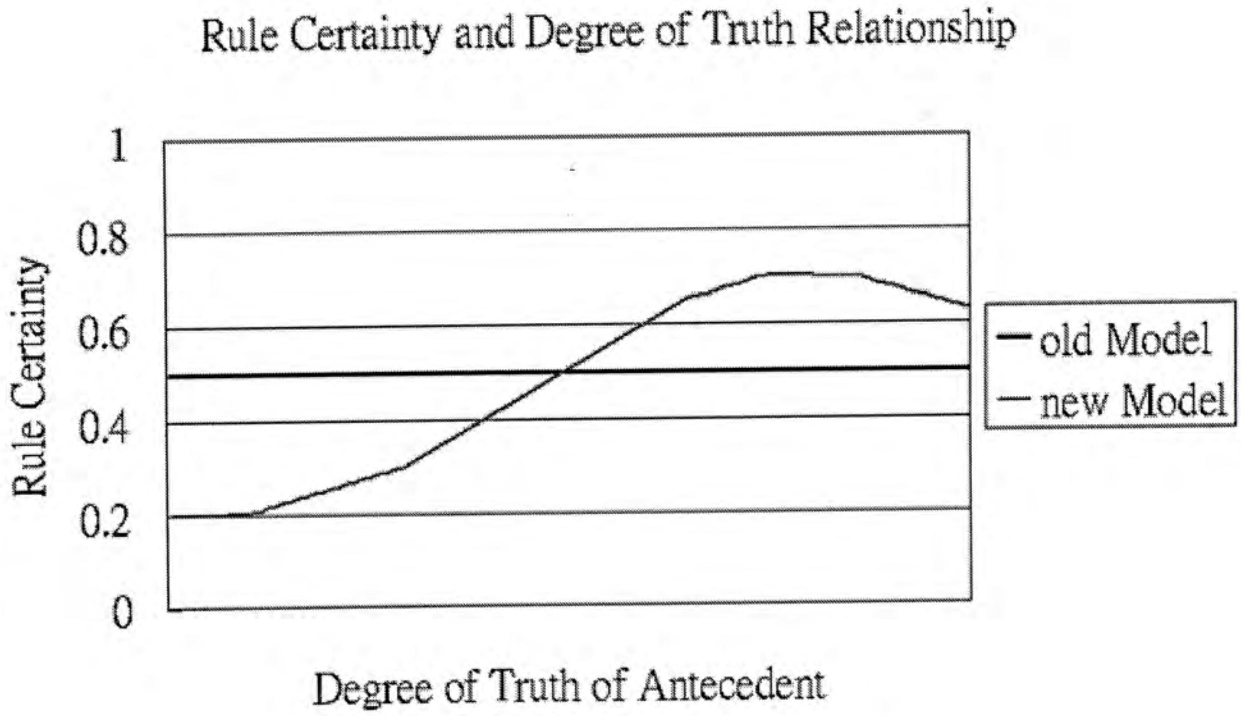

Figure 3.1: Certainty is not constant

The Figure 3.1 is an example of the certainty factor against the fuzzy value of one of the antecedents. This figure illustrates that the rule certainty is variate when the fuzzy value of the antecedent is changing. Their relationship can be represented by a mapping function. For different problem, or even different cases, we can use a tailor-made mapping function (called as certainty function γ) to facilitate the construction of a good model.

Besides, the above figure only describes one of the antecedents. To extend this concept, we could promote the dimension to N antecedents. In other words, this dynamic certainty can then be expressed as a form of function. If the rule has N antecedents, then its dynamic certainty μ could be in the form:

$$\mu_{dynamic} = \gamma(w'_1, w'_2, \ldots, w'_N, p_1, p_2, \ldots, p_N)$$

In the above expression, we can see that the dynamic certainty is determined by the fuzzy value of the antecedents and another set of weighings. A new set of weighings has been used in this expressions for determining the dynamic certainty, it is because the contribution of weighings on the "probability of result" should be different from that on the "certainty of result". As a result, the original set of the weighings could not be used in this expression. Besides, during the learning process, the two sets of weighings can be trained independently. This differentiation can give an effective learning time. Also, some system could have a greater tolerant percentage error on the certainty, in this case, the user can only train the rule weighing set (W). This gives the flexibility to the users in order to facilitate their own requirements.

The definition of this dynamic certainty - $\mu_{dynamic}$ is ranged from zero to one, $[0, 1]$. This range would then be consistent to the traditional model and the other currently used artificial intelligence theories. As a point of view on research field, those important theories are still hold and they can be still applied to enhance the current system. Moreover, the certainty function γ can be easily modelled by some standard and famous mathematical model such as the tri-geometrical function (e.g. sin x, cos x, tan x, etc ...) which are also ranged between zero and one. This range definition is also easier to be understood, its concept is more or less similar as the degree of truth table defined in (Section 4.1).

This formalization of the dynamic certainty is compatible with the old model. If this certainty function γ is a constant function, then the resultant effect would be the same as the original FPN model.

$$\mu_{constant} = C \qquad \text{where } C \text{ is a real number } \in \mathbf{R}$$

In most of the problems in this real world, it is common that "one plus one is not equal to two". Each individual could has its own contribution or stimulation in a particular problem. In other words, two or more criteria could result from a different effect, it could be better or worse which can be called as stimulation or suppression. The criteria could enhance or suppress the resultant effect. If the problem has such characteristic, the function γ would properly be a non-linear function. This idea is totally different from the traditional petri net model. In current model, the certainty factor (degree of truth) is defined as a constant when we setup the rule-based system. Throughout the system reasoning or system training, this certainty factor would not be modified. Most of the people adapt to agree this model because it can solve most of the problems. However, when we think more about the generic world, some of the algorithm would need to handle special cases, these special cases would properly come out because of the imperfect model representation for those cases. In order to reduce handling such special cases, it is worth to try to modify the current model and to simulate those special cases. As a result, we try to integrate this new component, *dynamic certainty* γ, in the traditional petri net model.

3.1.2 Examples

In order to understand more about our new model, it is good to illustrate by an example. Here are some of the examples in the medicine knowledge area.

Case 1

In medicine knowledge, it recently incorporates both the Western Medicine and the Chinese Medicine. This usually results in a better effect in helping patients. In this example, we model the function γ in the form as the following:

$$\gamma(\theta) = \frac{1 - e^{-b\theta}}{1 + e^{-b\theta}} \qquad \text{where } \theta = \sum w_i p_i, \qquad b = \text{ convergency rate}$$

This function is an increasing and continuous function. Here, we define a simple fuzzy membership function for each condition. In this example, we model the function γ has $b = 3, w_1 = 0.7, w_2 = 0.3$

In Figure 3.2, it is a simple rule representation using petri net model. With the above parameters, we could model the knowledge as follows:

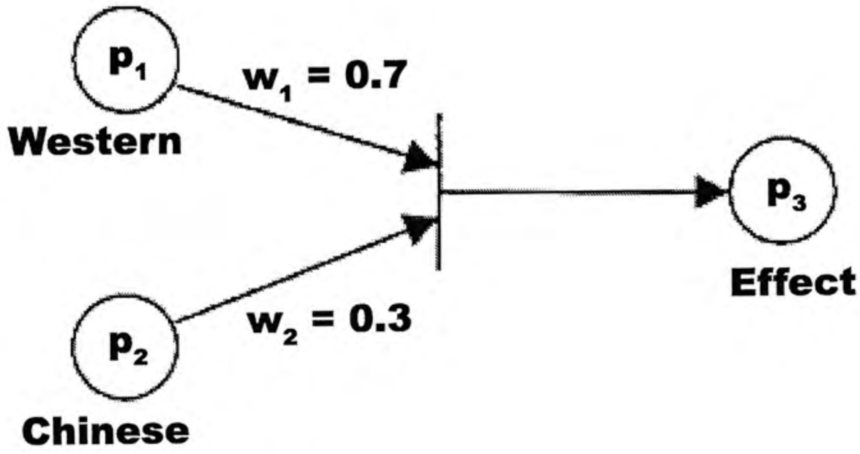

Figure 3.2: new FPN model: Example 1

Western (p_1)	Chinese (p_2)	μ	Diagnosis Effect (p_3)
0.2	0.2	0.5371	0.1074
0.2	0.5	0.7818	0.2267
0.2	0.8	0.9051	0.3439
0.5	0.2	0.7818	0.3205
0.5	0.5	0.9051	0.4526
0.5	0.8	0.9603	0.5666
0.8	0.2	0.9051	0.5611
0.8	0.5	0.9603	0.6818
0.8	0.8	0.9837	0.7871

As shown above, the certainty factor μ is increasing with the antecedents having greater values and thus results in a non-linear increasing function for the fuzzy value of consequence p_3. This effect can be trained by modifying the parameter b in the certainty function. Though the non-linear property of the effect on p_3 can be represented by a non-linear function in old model, but the dynamic certainty cannot.

In this example, there are only two antecedents p_1 and p_2. Here $W = W'$, this example can also illustrate that the different certainty weighting could result in the "stimulation" effect to help on the decision of best reasoning path.

Besides, if we model the certainty function γ = constant. Then this system would be the same as the traditional petri net model. Therefore, this evolution of the petri net model can also be compatible to the old model. Moreover, the new model can facilitate much more features than the old one.

Case 2

In this example, we would like to show the effect of "stimulation" when more criteria take part in the rule reasoning process.

In this system, we have the parameters: $w_{11} = w_{12} = w_{21} = w_{22} = 0.5, b_1 = 2, b_2 = 1.5$. That is, all nodes have the same weighting, but each rule has different stimulation effect.

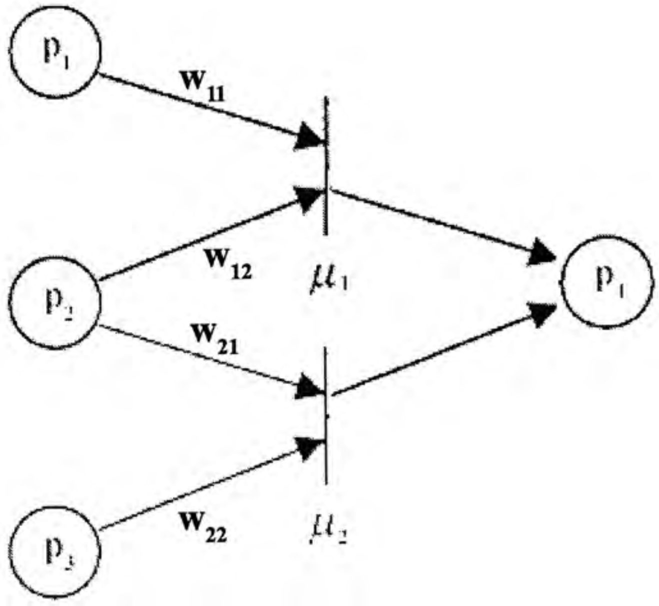

Figure 3.3: new FPN model: Example 2

No.	(p_1)	(p_2)	(p_3)	Rule 1 (μ_1)	Rule 2 (μ_2)	Effect (p_4)	Best Path
1	0.2	0.2	0.2	0.3799	0.2913	0.3100	Rule 1
2	0.2	0.2	0.5	0.3799	0.4816	0.3430	Rule 2
3	0.2	0.2	0.8	0.3799	0.6351	0.3775	Rule 2
4	0.2	0.5	0.2	0.6044	0.4816	0.3430	Rule 1
5	0.2	0.5	0.5	0.6044	0.6351	0.3775	Rule 2
6	0.2	0.5	0.8	0.6044	0.7509	0.4134	Rule 2
7	0.2	0.8	0.2	0.7616	0.6351	0.3775	Rule 1
8	0.2	0.8	0.5	0.7616	0.7509	0.3775	Rule 1
9	0.2	0.8	0.8	0.7616	0.8337	0.4502	Rule 2
10	0.5	0.2	0.2	0.6044	0.2913	0.3430	Rule 1
11	0.5	0.2	0.5	0.6044	0.4816	0.3430	Rule 1
12	0.5	0.2	0.8	0.6044	0.6351	0.3775	Rule 2

No.	(p_1)	(p_2)	(p_3)	Rule 1 (μ_1)	Rule 2 (μ_2)	Effect (p_4)	Best Path
13	0.5	0.5	0.2	0.7616	0.4816	0.3775	Rule 1
14	0.5	0.5	0.5	0.7616	0.6351	0.3775	Rule 1
15	0.5	0.5	0.8	0.7616	0.7509	0.3775	Rule 1
16	0.5	0.8	0.2	0.8627	0.6351	0.4134	Rule 1
17	0.5	0.8	0.5	0.8627	0.7509	0.4134	Rule 1
18	0.5	0.8	0.8	0.8627	0.8337	0.4134	Rule 1
19	0.8	0.2	0.2	0.7616	0.2913	0.3775	Rule 1
20	0.8	0.2	0.5	0.7616	0.4816	0.3775	Rule 1
21	0.8	0.2	0.8	0.7616	0.6351	0.3775	Rule 1
22	0.8	0.5	0.2	0.8617	0.4816	0.4134	Rule 1
23	0.8	0.5	0.5	0.8617	0.6351	0.4134	Rule 1
24	0.8	0.5	0.8	0.8617	0.7509	0.4134	Rule 1
25	0.8	0.8	0.2	0.9217	0.6351	0.4502	Rule 1
26	0.8	0.8	0.5	0.9217	0.7509	0.4502	Rule 1
27	0.8	0.8	0.8	0.9217	0.8337	0.4502	Rule 1

In this example, the node 2 (p_2) takes part into both Rule 1 and Rule 2. In this system model, the other two nodes (p_1, p_3) would contribute to determine which rule is the best reasoning path. Since we could model each rule has its own function representation for the rule certainty, this certainty function γ could be in different forms of the expressions. The function can be polynomial, exponential or even other types of function, which would depend on the particular problem.

Therefore, the *dynamic certainty* could take part into the stimulation of the rules even each node having the same weighting. If the dynamic certainty has a non-linear function, even each node has the same weighting, they can give a non-linear result, which can then model the stimulation effect for the rule.

Referring the case No.24, $p_2 = 0.5, p_1 = p_3 = 0.8$, which gives the result $\mu_1 = 0.8617, \mu_2 = 0.7509$. Clearly, p_2 is the core antecedent in this system. With the modelling of dynamic certainty, each rule in this system now would have greater dependency compared with the traditional model.

To achieve a more clear concept, we could modify the reasoning technique of this petri net model. Here, we introduce one of the possible evolutions:

The calculation of the fuzzy value of the consequence in rule inferencing

$$\text{in the traditional model}: \quad y_k = Min(y_{j1}, y_{j2}, \cdots, y_{jn}) * \mu_i$$

$$\text{in the new model}: \quad y_k = \alpha_{All} * \mu_{All}$$

The new rule inferencing can then ignore the rule certainty which is just involving the properties of the antecedents. In such modelling, since the certainty and the fuzzy value are now *mutually exclusive* to each other, we can treat there are two sets of the concept (the probability and the certainty) in each rule of the knowledge representation.

In point of view in the learning of the system, the reasoning process for both the consequence (the traditional function α) and the *dynamic certainty* (the new suggested component γ) are important, because they both are the factors of deducing the conclusion.

3.2 Advantages

3.2.1 Best reasoning

With the dynamic certainty μ in the knowledge model, even the same rules are fired in the system, each rule now would have different certainty with different fuzzy values of the antecedents. Therefore, the best reasoning would now depend on the fuzzy value of antecedents and their corresponding weight in the rule. This dynamic feature can model much more complex system and the model can also be more understandable and reasonable.

In our suggested new component, the dynamic certainty factor $\gamma : \alpha, W\ to[0, 1]$, is the function in terms of the fuzzy value of antecedents α and the corresponding weighting sets W in the rule. Therefore, the effect of each antecedent can be positive or negative according to the sign of their weighings. If we would represent some more complicated problem, the certainty function can use another set of weighting value ($W_\mu = \{w'_{11}, w'_{12}, \ldots, w'_{1j_1}, w'_{21}, w'_{22}, \ldots, w'_{2j_2}, w'_{i1}, w'_{i2}, \ldots, w'_{ij_n}\}$). In this way, the certainty value can be more independent to the probability of the antecedents, and thus the induced fuzzy value and the certainty can then classified more clearly.

With this introduction of dynamic certainty factor γ, the knowledge system model can be regarded as a general graph, by using the algorithm in graph theory, the shortest/longest path can be found with the known value of edge value. Since the edge value in the graph have different values in each problem, which depend on the initial fuzzy value of the facts (antecedents). As a result, for each case given to the system model, a general graph would be given with the weighted edges generated after the system reasoning. Hence, when two similar cases happen, they would have the similar graph with the same nodes and the same edges, however, their edge weights would be most likely not the same. In traditional FPN model, the same graph of the same nodes and the same edge weight values would be generated in such cases. If such case happens, we cannot differentiate the individual cases. In other words, different cases would result the same conclusion in the traditional expert system model. Certainly, it is not good for data analysis and other further research.

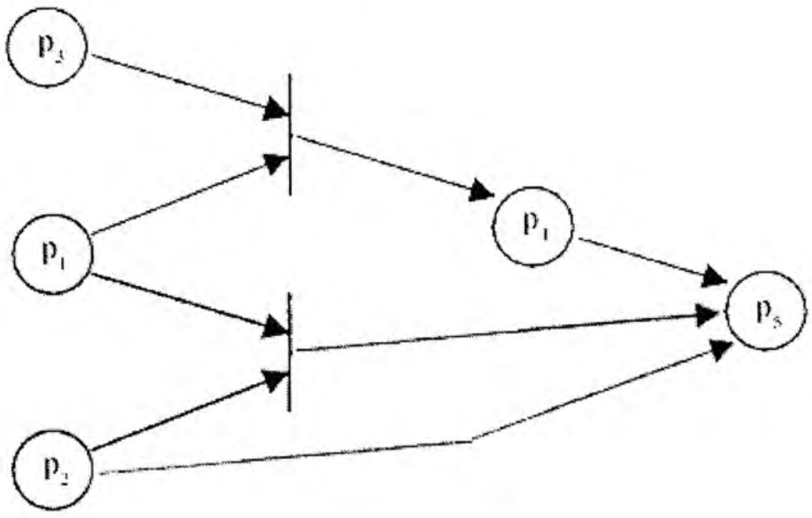

Figure 3.4: Best Reasoning Path

The Figure 3.4 gives a simple example to illustrate problems found in traditional model. Suppose the system consists of the following rules:

- R_1: If p_1 and p_2 Then p_5, ($\mu_1 = 0.45$)
- R_2: If p_2 and Then p_5, ($\mu_2 = 0.50$)

- R_3: If p_1 and p_3 Then p_4, ($\mu_3 = 0.8$)
- R_4: If p_4 and Then p_5, ($\mu_4 = 0.6$)

Suppose all the rules are fired, there would have totally 3 paths to get the goal node p_5. The first route ($[p_1, p_3] \rightarrow p_4 \rightarrow p_5$) has the certainty $\mu_3 * \mu_4 = 0.48$, while the second route ($[p_1, p_2] \rightarrow p_5$) has the certainty $\mu_1 = 0.45$ and the third route ($p_2 \rightarrow p_5$) has the certainty $\mu_2 = 0.5$. In case, the fuzzy values of the antecedents p_1, p_2, p_3 would result the same fuzzy value of consequence p_5, thus the best reasoning path would be the third route ($p_2 \rightarrow p_5$) since it has the greatest certainty value . Since all the rule certainties are constant in the system model. Therefore , the best reasoning path is already determined if all rules are fired. In this example, it is clearly that p_1, p_2 actually gives a greater value than p_2 to finally return the same value of p_5. So, p_1, p_2 together should give a positive effect on the conclusion p_5, nevertheless, the final fuzzy value cannot represent this effect due to the "constant certainty". Thus, this rule reasoning could result a wrong interpretation.

Moreover, the concept of certainty and the fuzzy value should be different in human thinking. There is not such differentiation in traditional model because of the simplicity. Therefore, the decision of the best reasoning path in the traditional model cannot solve some of the problems.

Now, let us try by using the model with *dynamic certainty*. If we model each rule certainty with a function which is in terms of the fuzzy value of antecedents and their corresponding weighings. Thus, $\mu_{1(new)} > \mu_{1(old)}$ and $\mu_{1(new)} > \mu_{2(new)}$.

Because $\mu_{1(new)} > \mu_{1(old)}$, even $\alpha_{old}(p_1, p_2) = \alpha_{new}(p_1, p_2)$, the final fuzzy value of the consequence p_5 would be greater, and the best reasoning path would then be the second route ($[p_1, p_2] \rightarrow p_5$). In the case, the system can then interpret a proper reasoning similar to human thinking.

3.2.2 Independency

In the traditional model, when a rule is fired, its consequence fuzzy value is the product of the rule certainty and the fuzzy value of one of the antecedents:

$y_k = Min(y_{j1}, y_{j2}, \ldots, y_{jn}) * \mu_i$.

With this definition of reasoning, either one of the antecedent certainty would enter into the resultant fuzzy value. All other antecedents are ignored in the consequence. However, in the nature world, sometimes two or more factors would have stimulations to each other and then causes unexpected result. Therefore, in modelling an expert system, it is better to model this kind of 'stimulation' in the model to represent such knowledge.

The Figure 3.5 can easily illustrate the special case, that is, the consequence certainty would be greatly dependent on the antecedent which has the lowest fuzzy value in a conjunctive rule. Although it is correct and reasonable, this algorithm cannot show the contribution of entire antecedents in the rule. In this way, when there are two different rules, but which are both dominated by the same antecedent, this would lead to a great correlation between these two rules, because of the same dominator.

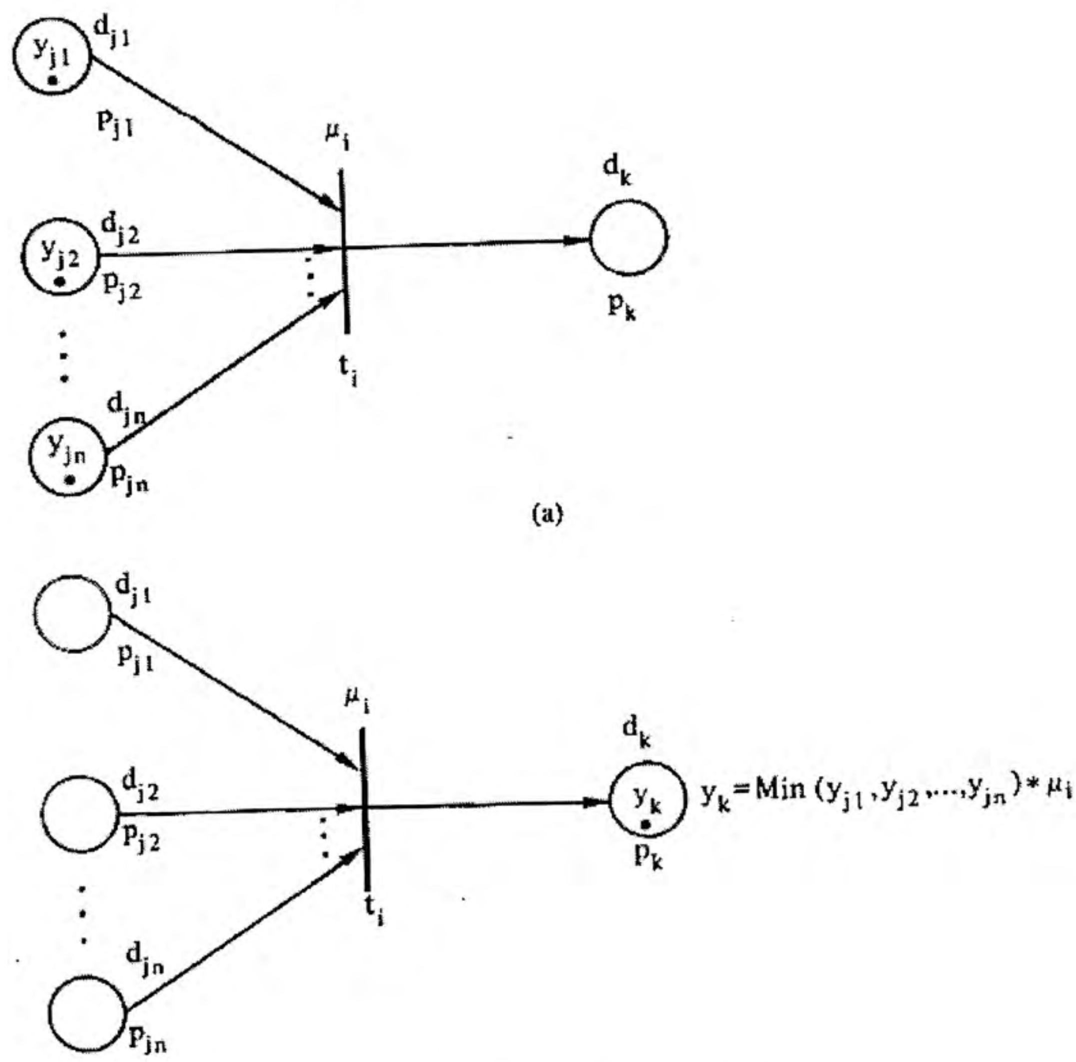

Figure 3.5: FPN reasoning
(a) Before firing transition t_i. (b) After firing transition t_i

Let us consider a simple example:

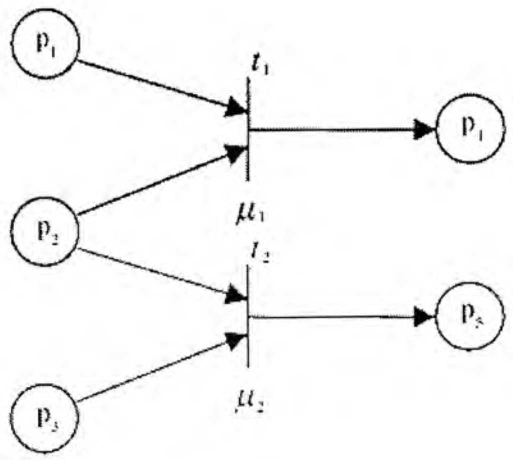

Figure 3.6: FPN reasoning: Special Case in Old Model

In the example (Figure 3.6), suppose both two rules are fired. If the antecedents $p_1 = 0.1, p_2 = 0.98, p_3 = 0.15$, the result fuzzy values of $p_4 = 0.1\mu_1$ and $p_5 = 0.15\mu_2$. Here, it is easy to note that even p_2 has a comparatively high fuzzy value in each rule, the resultant fuzzy values of the consequence are still quite low which is due to the low fuzzy value of one of the antecedents. If the rule has more such 'high value' antecedents, their values or information are lost because of this reasoning algorithm.

Let us think about when there exists a extremely low fuzzy value of antecedent and it is also the antecedent in most of the rules in the system model. Such case introduces one antecedent would become the majority reasoning effect which causes the rule sets lose their own characters.

With the potential of this problem, the *dynamic certainty* could help to reduce such effect significantly. As the certainty now is a function of the fuzzy value of antecedents and their weighting, **all** the antecedents in the rule now could contribute their values in the certainty factor, but not only one antecedent determines the certainty factor. As a result, the certainty factor could be more representative in the system reasoning.

3.2.3 Interaction effect

In traditional FPN model, the relative similarity of the antecedents is usually determined and dominated by one of the all antecedents. For sure, this is a simple method during the reasoning process and this can speed up the calculation time.

Nevertheless, in real situation, we always emphasize the **interaction** between people and the communities. That is the intercross communication between one individual and another individual, or even between several individuals.

Example. There are three workers **A**, **B** and **C**. **A** spends *15* days to complete a task individually, while **B** spends *7* days for the same task, and **C** spends *10* days for the same case. If **A** and **B** work together, they need *10* days to finish the same job. While if **A** and **C** work together, they spend *9* days. And when **B** and **C** work together, they spend *5* days. For the last case, all three of them work together, they just spend *4* days to complete the task.

In the above example, we observe that the resultant job efficiency between two/three workers is not just equal to the addition of each individuals. This kind of phenomenon we called as **interaction**. The *key* idea of this concept is the *invisible properties* between the individuals or among the groups of communities.

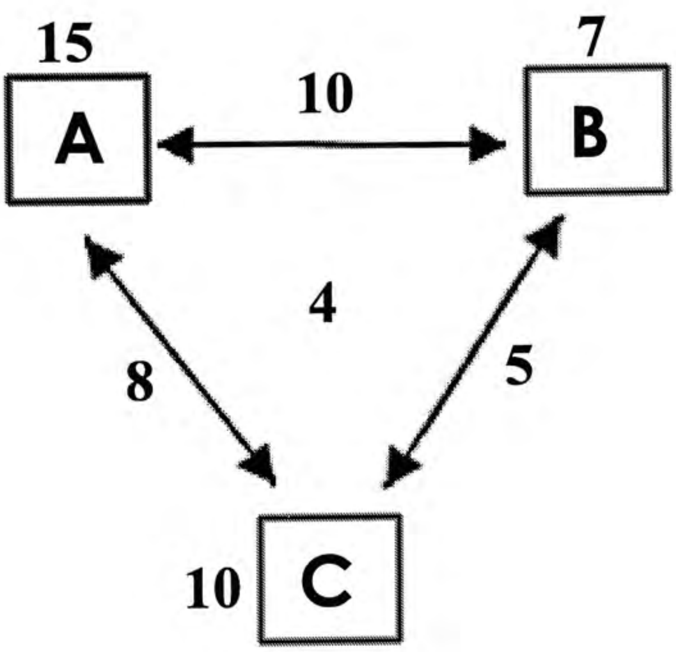

Figure 3.7: Interaction effect

$$\{A,B\}=10 \quad \min[A,B]=\min[15,7]=7 \quad \Rightarrow \{A,B\}\geq \min[A,B]$$
$$\Rightarrow Negative$$
$$\{A,C\}=8 \quad \min[A,C]=\min[15,10]=10 \quad \Rightarrow \{A,C\}\leq \min[A,C]$$
$$\Rightarrow Positive$$
$$\{B,C\}=5 \quad \min[B,C]=\min[7,10]=7 \quad \Rightarrow \{B,C\}\leq \min[B,C]$$
$$\Rightarrow Positive$$
$$\{A,B,C\}=4 \quad \min[A,B,C]=\min[15,7,10]=7 \quad \Rightarrow \{A,B,C\}\leq \min[A,B,C]$$
$$\Rightarrow Positive$$

In the example, it can illustrate that the **interaction** effect can be *positive* or *negative*. That means the defined result can be better or worst than each individual. Therefore, during the evaluating the expected result, we have to consider the power set of the individual conditions. Actually, we can say such *invisible properties* hidden in the **interaction** is another *condition* in the rule, we just cannot classify that condition only.

It is possible that the result for combination of the individuals can be the same as that for each individual. If such case happens, we can choose either one of the reasoning path. In the past computer system, the concept of *interaction* is seldom mentioned. It would be because the significant of the differences is very small. However, it does exist in most of the real situations. Thus, it is important to implement this component in the inferencing system.

3.3 Chapter Summary

In this chapter, The new idea of *dynamic certainty* has been introduced. The key concept on this evolution is to differentiate the interpretation of "probability of result"' and "certainty of result". In traditional model, only the first item, that is probability, is considered. This traditional approach is correct for reasoning in common cases. Nevertheless, on the decision of rule firing in a complex expert system. The determination criteria of the rule firing should be the certainty but not the probability of result in fact. As a result, the differentiation between the "probability of result" and the "certainty of result" is necessary.

Our new design for the *dynamic certainty* is detailedly defined in Section 3.1. In Section 3.1.2, some examples are presented with the usage of the new model. With this innovative evolution model introduced, its advantages and benefits are briefly described in the Section 3.2.1 for best reasoning, Section 3.2.2 for independence and Section 3.2.3 for interaction effect.

Chapter 4

Experiment

In this research project, the goal is to integrate the new fuzzy petri net (FPN) model and the Chinese medical knowledge and then a Chinese medical expert system . For Chinese medical knowledge, we would focus on the Chinese acupuncture.

With the references of the acupuncture expert and paper resources, we would concentrate on several common illness:

(1) Constipation, (2)Diarrhoea, (3)Shigellosis

Among the above three sickness, they have some common symptoms. When there is a patient having those symptoms, doctor needs to determine which sickness the patient got for proper healing approach. With this reason, we have constructed a FPN system to simulate a Chinese medicine expert on diagnosis based on Chinese medicine knowledge. In general, the suggested symptoms is not the only criterion on medical diagnosis, but also including some other factors (such as the health history of the particular patients and health history of his relatives, etc.). Nevertheless, the suggested system structure can be used as a reference on medical diagnosis. Meanwhile, we would like to use this example to illustrate the new FPN model.

The common symptoms of constipation, diarrhoea and shigellosis are :

- Body condition
- Tongue color
- Tongue texture
- Faeces texture
- Abdomen Painfulness
- Pulse rate

4.1 Transformation Definition

Degree of Truth Table

Truth Scale	Numerical Intervals
Always true	[1.00,1.00]
Extremely true	[0.95,0.99]
Very true	[0.80,0.94]
Considerably true	[0.65,0.79]
Moderately true	[0.45,0.64]
More or less true	[0.30,0.44]
Minority true	[0.10,0.29]
Minimally true	[0.01,0.09]
Not true	[0.00,0.00]

Transformation of symptoms to numerical number

Symptom	Symptom Scale	Numerical Intervals
Body	Serious	[0.90,1.00]
	Bad	[0.80,0.89]
	Defect	[0.60,0.79]
	Unwell	[0.45,0.59]
	Normal	[0.30,0.44]
	Good	[0.15,0.29]
	Excellent	[0.00,0.14]
Tongue Color	Very red	[0.90,1.00]
	Normal red	[0.75,0.89]
	Pale red	[0.60,0.74]
	Yellow	[0.45,0.59]
	Pale yellow	[0.30,0.44]
	Very pale color	[0.00,0.29]
Tongue Texture	Thick moisture	[0.90,1.00]
	Moisture	[0.70,0.89]
	Normal	[0.5,0.69]
	Dry	[0.35,0.49]
	Very dry	[0.00,0.34]

Transformation of symptoms to numerical number (Con't)

Symptom	Symptom Scale	Numerical Intervals
Faeces Texture	Very dry and very hard	[0.90,1.00]
	Dry and hard	[0.75,0.89]
	Hard	[0.6,0.74]
	Normal	[0.40,0.59]
	Sparse form	[0.30,0.39]
	Liquid form	[0.00,0.29]
Pulse Rate	Very rapid	[0.90,1.00]
	Rapid	[0.80,0.89]
	Fast	[0.55,0.79]
	Normal	[0.45,0.54]
	Below normal	[0.30,0.44]
	Weak	[0.00,0.29]

System Architecture using Fuzzy Petri Net

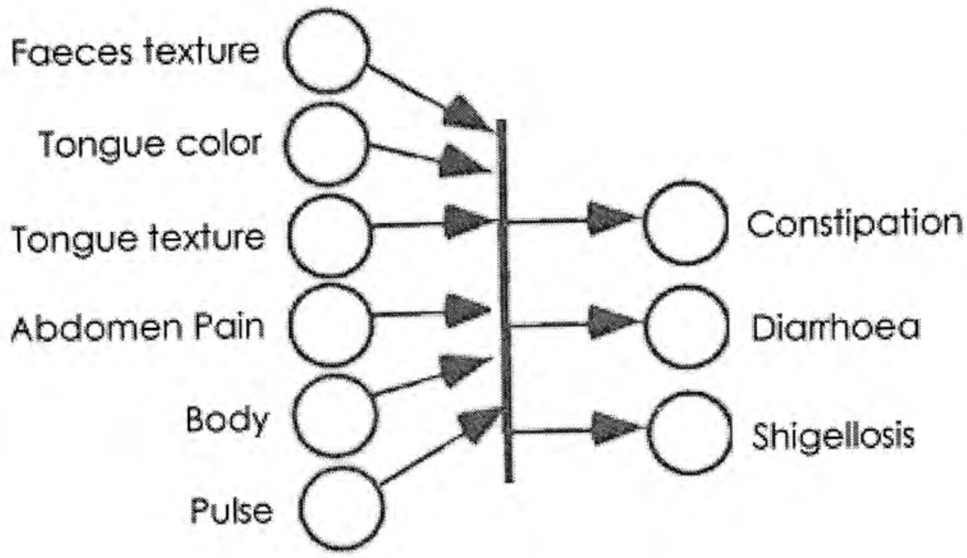

Figure 4.1: Chinese medicine system architecture

The designed system is mainly based on the fuzzy petri net model. Since the proposed information is constructed of a comparatively simple structure, the following examples could be easily illustrated the functionalities of the new model.

In Chinese medicine, the critical task is the procedure of diagnosis. Once a doctor determine or ensure which illness, the solution or the healing way is deterministic.

Rules in the System

Body	Tongue Color	Tongue Texture	Faeces Texture	Pulse	Constipation
0.6	0.7	0.4	0.9	0.5	0.9
0.6	0.5	0.6	0.6	0.6	0.8
0.7	0.2	0.2	0.7	0.1	0.6
0.7	0.4	0.2	0.7	0.2	0.7
0.9	0.4	0.1	0.7	0.4	0.7

Rule No.	Body	Tongue Color	Tongue Texture	Abdomen	Pulse	Diarrhoea
1.	0.5	0.4	0.5	0.9	0.6	0.9
2.	0.6	0.7	0.7	0.8	0.4	0.95
3.	0.3	0.6	0.8	0.9	0.5	0.8
4.	0.7	0.3	0.2	0.9	0.2	0.75
5.	0.8	0.6	0.5	0.8	0.6	0.7
6.	0.9	0.4	0.3	0.5	0.2	0.65

Rule No.	Body	Tongue Color	Tongue Texture	Abdomen	Pulse	Shigellosis
1.	0.6	0.7	0.7	0.8	0.6	0.75
2.	0.7	0.5	0.6	0.8	0.4	0.8
3.	0.8	0.7	0.7	0.95	0.5	0.85
4.	0.7	0.4	0.6	0.8	0.4	0.75

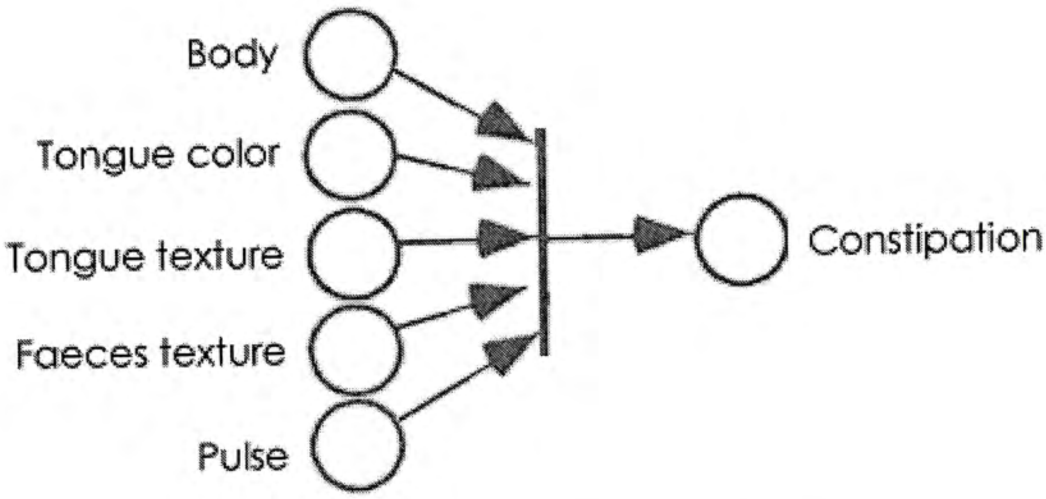

Figure 4.2: Example : Rule structure (a)

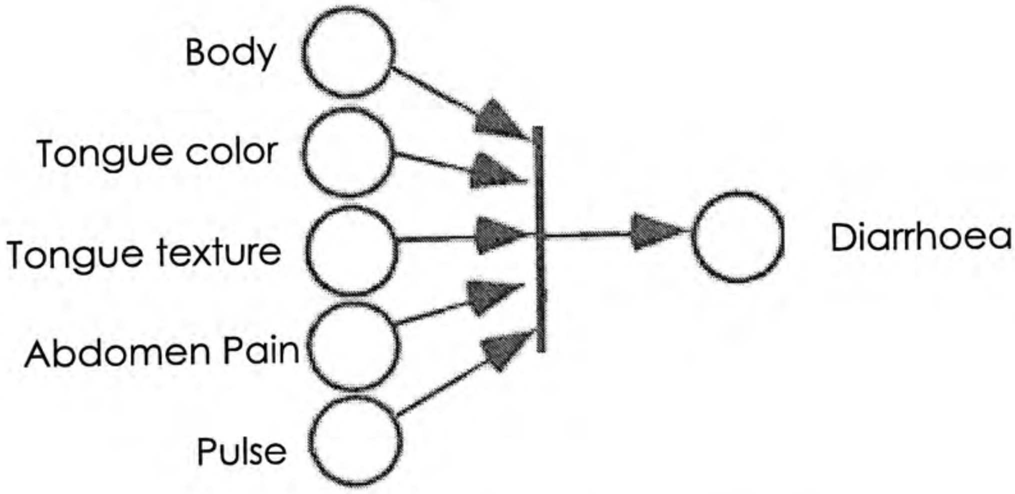

Figure 4.3: Example : Rule structure (b)

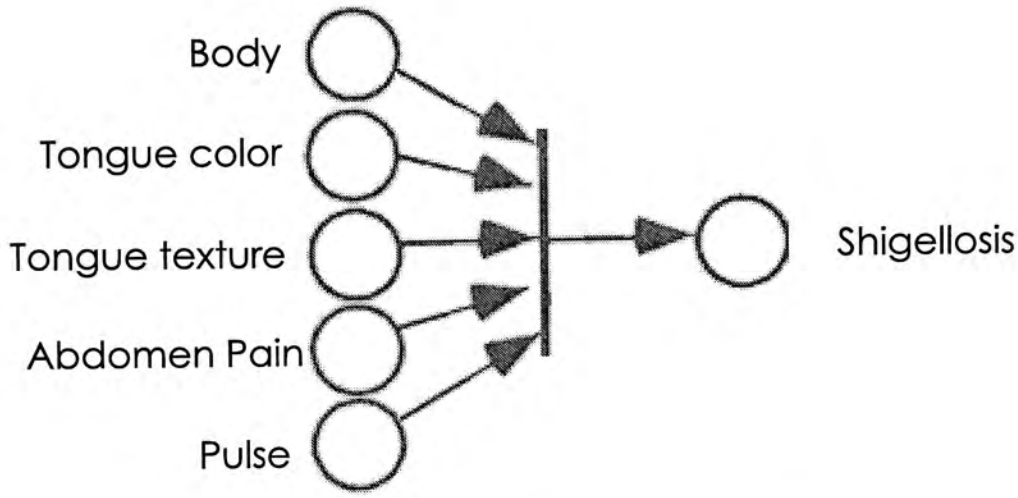

Figure 4.4: Example : Rule structure (c)

From the structure diagram, the rules can be mainly classified into 3 groups (by the illness) : (1) Constipation, (2)Diarrhoea, (3)Shigellosis

The previous table shows the details of the knowledge in the forms of the FPN model, while the Figures 4.2, 4.3 and 4.4 illustrate the FPN structure. The information, and the case details were extracted from the real medical cases. All the rules are constructed based on the medical information from reference books.

4.2 Case Study

4.2.1 Example 1

This is a forward inferencing example. Based on the pre-defined model in Section 4.1, with the initial value of each of the antecedents, the system can then determine which rule(s) would be fired. And finally, the system can give the value of consequences, which in turns the conclusion can be deduced.

One of the examples Details

Body	: 0.46
Tongue Color	: 0.48
Tongue Texture	: 0.45
Faeces Texture	: 0.40
Pulse	: 0.41
Expected result for constipation	: 0.38

For the dynamic certainty function, we firstly suggest to use a linear expression, $\mu = \sum w_i p_i$.

In the first step, we divide two data sets which are used for training (D_{train}) and for testing (D_{test}).

Next, we then firstly assign an initial value to weighings for dynamic certainty before learning. We use the **minimum error difference** algorithm to learn the certainty weighings W'. There are totally 50 cases for rule training, while there are another 100 cases for testing the trained rules.

In our experiment, we measure the error percentage as a reference, so that the comparison could be reliable and convenient. The error percentage is defined as :

$$\frac{\text{calculated result-expected result}}{\text{expected result}}$$

We perform the same reasoning process for the 100 testing cases. The result is summarized in Figure 4.5:

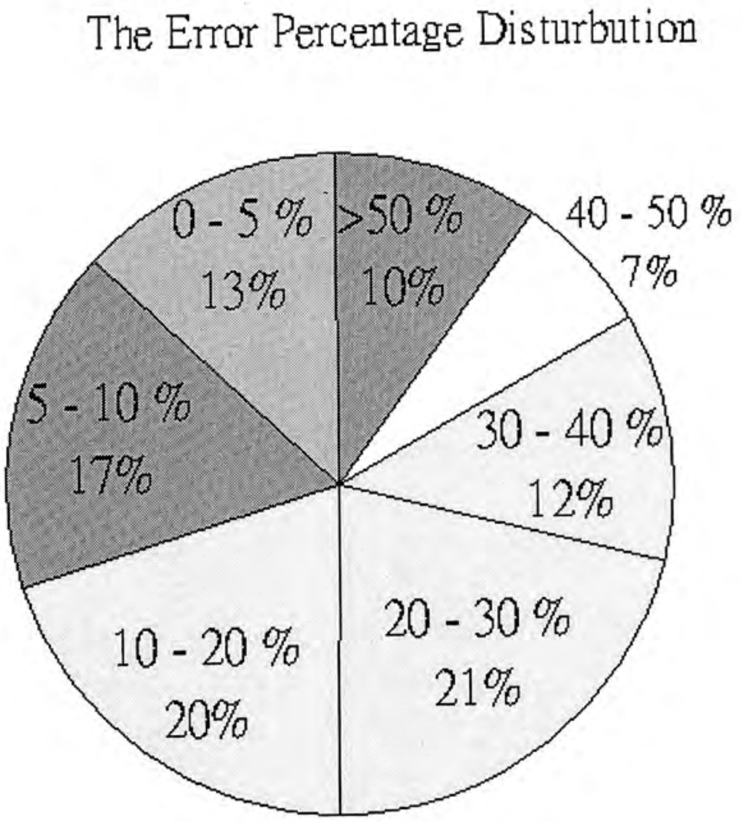

Figure 4.5: Error Difference from the expected result (First Trial)

From Figure 4.5, the error percentage with 0-5% is of 13%, that with 5-10% is of 17%, that with 10-20% is of 20%, that with 20-30% is of 21%, that with 30-40% is of 12%, that with 40-50% is of 7%, and finally error percentage over 50% is of

10%.

From the above statistics, the result of the first attempt is not very appreciate. Most of the testing cases result a large error percentage even over 20%.

In general, until reaching the optimal point, more training cases would increase the correctness of the training model.

4.2.2 Example 2

In this example, we would try to improve the performance of this model. Linear summation was used for evaluating the certainty value in the previous example. This choice of expression model can be different for different particular problem sets. Hence, we would like to use another expression model to further simulate as good as the real situations of the problems.

In the previous example, the final conclusion is the product of fuzzy value of antecedents and the certainty value. Since our *dynamic certainty factor* is also a function of fuzzy value of antecedents, in other words, the conclusion calculation involves this component twice and thus the antecedents are *overweighed.* Consequently, the antecedents should contribute less in the certainty function.

In this example, the certainty function is :

$$\mu = \sum \frac{w_i w_i'}{w_i + w_i'} p_i$$

where w_i s rule weighing, and w_i' is certainty weighing

We would like to emphasis that the above specific expression is still a suggested solution. There would have some other forms of expression that could give better results.

With the same model structure and the same inferencing algorithm, the resultant figures are pleasing and acceptable. There is a great improvement that there are 89% testing data within 10% of error percentage. This result can show that our model is suitably useful and it can also give a reasonable result with an acceptable error percentage.

The summarized result is shown as Figure 4.6 :

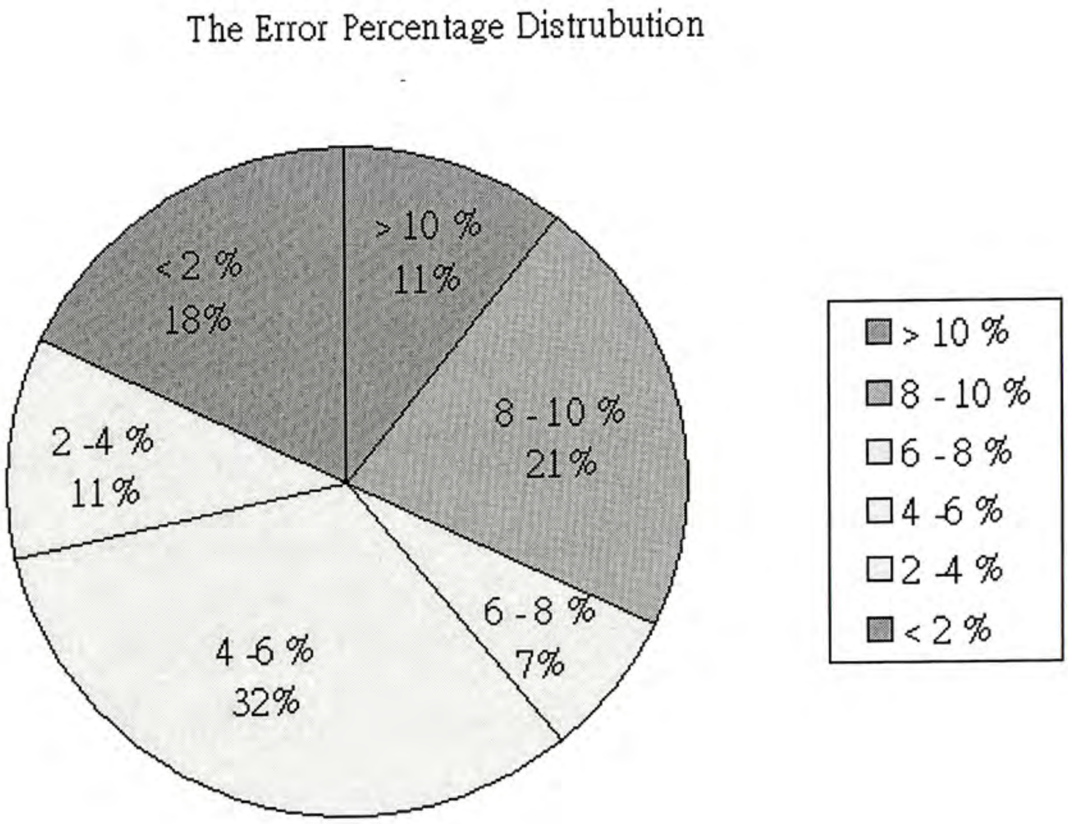

Figure 4.6: Error Difference from the expected result

From the Figure 4.6, majority of the testing cases are within 4-6% of error percentage. Indeed, if we count the process of transformation from linguistic form to digital form or vice versa, then this error percentage can be regarded as insignificant. Hence, we can conclude that this model is applicable and feasible on the modelling of an expert system.

This example shows that the *certainty function* can be in different forms of expression. This depends on the problem sets, the training cases and the testing cases.

4.3 Analysis

4.3.1 Comparisons

Simulation in traditional FPN model

As we know that the current FPN model is already well-developed, the same problem can be applied on the traditional FPN model (i.e. without dynamic certainty factor). Hence, we would like to show the results for both models and thus we can further improve by such kind of analysis.

With the same data sets, we plug the data into a traditional model. Again, there are totally 50 cases for rule training and 100 cases for testing the trained rules.

The reasoning results for traditional FPN model are as follows:

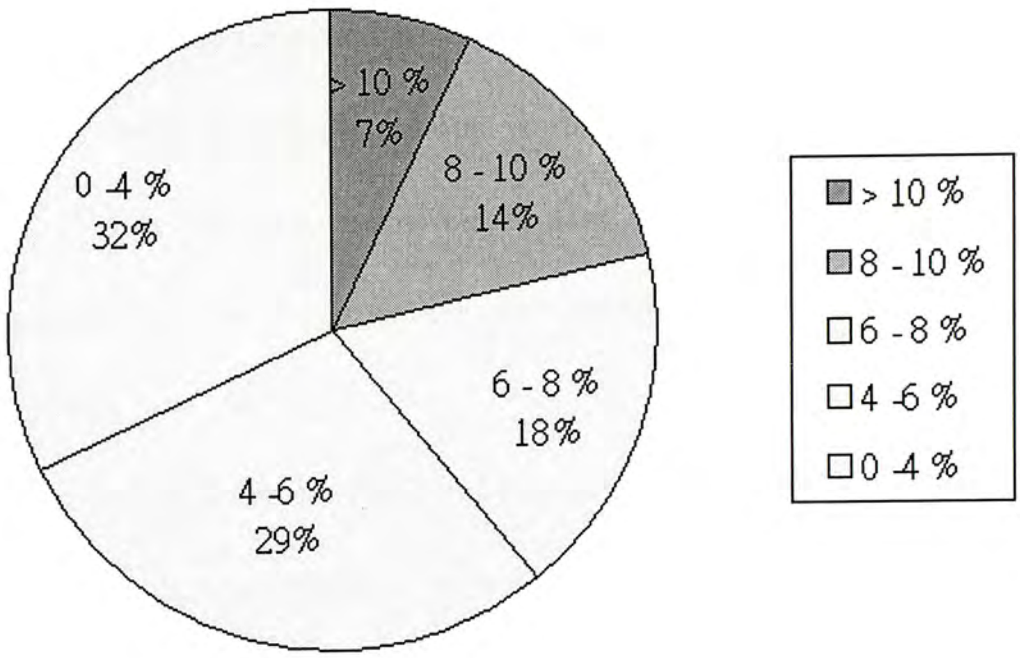

Figure 4.7: Error Difference (traditional FPN)

From the Figure 4.7, the results with using the traditional model is appreciate and satisfactory. This result shows that the traditional FPN is already good and general enough for the solution of most problems. However, in the point of view of the human understanding, this model so far is quite plain and simple.

Comparison

From the previous results of the two models, they both show good outcomes. Both of them could give the results with over 80% of accuracy within our threshold. In our examples, both of the two models require the same input parameters to deduce the same kinds of outputs. In the viewpoint of accuracy, they seem to have no difference. Therefore, both models can be applied to most of the problem cases.

Indeed, the two models (traditional and new models) both have their own approaches and focusing points. The traditional model focuses on the input antecedents. It is because the conclusion is deduced from the antecedents during reasoning. While the new model would also concern about the fundamental knowledge background, as it can model the intrinsic properties by having a good certainty function.

In a brief summary, both models could solve the rule-based problems. Each of them has its own functionalities. In fact, there may have other benefits by using the dynamic certainty factors. Each problem would have its own characteristics (intrinsic properties), if we can model these factors, the solution would then be specific and tailor-made.

4.3.2 Discussion

The interesting motion of this research is the encouraging force on identification of **certainty** in our interpretation. We believe that **certainty** in human's decision should not be a constant, and even not be the same for different cases at the starting moment. Besides, this certainty value should vary and depend on some extrinsic information such as related environment parameters, users' historical record and even the feedback information.

It is not difficult to understand the above concept because it is just the nature approach in the thinking procedure of human mindset. Nevertheless, the relationship between the certainty and its dependencies is needed to be determined. The relationship can be simple or complex, that would be problem-dependent.

With the incorporation of the *dynamic certainty factor*, the entire structure is practically justifiable. From the observation in the examples, it needs special algorithm in order to find out a suitable expression to model this *dynamic certainty factor* for each particular problem. The methodologies can be in-born or discovered from real data sets. This would lead to another large area on researching purpose.

4.4 Chapter Summary

In this chapter, the Chinese medical knowledge is adopted into our innovative FPN. Section 4.1 has given the definitions of transformation used from linguistic information to numeric vales in our examples. The information we used is consulted from human experts and also from paper materials. Many examples are given in Section 4.2 which can illustrate that the our design model is feasible. Moreover, a brief analysis has been mentioned in Section 4.3.1, and some more discussions in Section 4.3.2. This section has compared the strengths and the weaknesses between the basic FPN and the new FPN (with dynamic certainty component). The experimental results could give the evidence on this innovative modification on FPN modelling.

Chapter 5

Conclusion

5.1 Final Summary

Chinese medicine nowadays becomes more and more popular in Hong Kong and even in foreign countries. With the success of the information technology application in Western medicine treatment, we do have passion applying the similar techniques on the area of Chinese medicine. Acupuncture is one of the large section in the Chinese medicine. Once we have a good diagnosis result, acupuncture can be directly applied with a standard approach. As a result, a good diagnosis algorithm is necessary in Chinese medicine expert system. In this way, with the given symptoms provided by the patients, the system is expected to tell us what kind of illness the patient is suffering. At the same time, it is a good time to organize well for the huge resources on Chinese medicine.

Fuzzy Petri Net (FPN) is a well-known research area in artificial intelligence. Many further researches on FPN are still very active in the current moment. Many researchers focus on various approach on learning algorithm, constructing different model for particular problems, etc. The numerous research projects on FPN shows that FPN has great research value and even not only in theoretical approach, but also practical point of view.

The main purpose of this research is the introduction of a new concept - *dynamic certainty factor*, which is modified from the *constant value* in the current model. In the past, every rule (transition) would be assigned a constant certainty value during system design. This *constant value* is usually an estimated value from human experiences, therefore it would have the possibility that a threshold of error difference. However, one of the problem solving techniques would be always choosing a solution with a relative high certainty, this can show that people do what they have more confidence on such action. Moreover, this "certainty" would usually change when the environment conditions change in real situation.

We have done the experiment of applying the new FPN model to a Chinese expert system. In fact, the Chinese medical knowledge have a nature and straight interpretation of diagnosis between different body systems within the entire human body. The characteristics of Chinese medical information are the vagueness and linguistic representation. Hence, fuzzy logic is very suitable to implement or computerize such features with good performance.

With the introduction of the suggested new component, the entire FPN model becomes more complicated. Concurrently, some other modifications would be also necessary.

5.2 Deficiency and Improvement

In this research project, all ideas are of high originality. The critical problem is the difficulty on collecting the realistic and systematic Chinese medical cases. Since Chinese doctors did not have systematic or regular medical data record as the usual practice as western doctors, we spent lots of the time to collect and process the loose, dis-organized linguistic information. It is very common that Chinese doctors use hand script to store the patients' medical records, this leads to the trouble on various research area.

Another important feature of Chinese medicine is the standpoint on human system, its framework emphasizes the maintenance of the entire body, rather than the each part of the body system. Therefore, in order to simulate as real as a Chinese medicine expert, the whole picture of all information should be implemented into it. This is another difficulty in this project. Since the resources are limited, we can just focus on some part of the information within the entire knowledge set.

In our research, the new model contains two sets of weighings for the fuzzy value and the certainty factor. This structure gives the ambiguity to the understanding of its **importance** to its transition. In usual practice, a higher weighing value indicates a higher importance when there is only one *weighing* in the calculation. This concept is very easy to be understood. In this way, some people would find difficulty in understanding the idea of having "two weighings" in one model representation. Indeed, each of the weighing would be corresponding to different factors. Nevertheless, the *weighings* would have more or less correlations. As a result, users should have a clear mind in the understanding of the specific problem and also the model structure.

With the two sets of weighings, the learning time is thus longer to reach an optimal result. This is unpreventable because an addition of the new component usually increases the processing time and the complexity. At the first beginning, we have tried to use **one set of the weighings** to handle both properties (rule and certainty). However, we found this would decrease the flexibility of each individual component. Besides, this cannot show the characteristics of the **dynamic certainty factor** in the model too.

With the time limitation on this research, we can only concentrate on several major tasks and can just target for several research ideas. Nevertheless, there are some possible improvements on our suggested proposal:

Currently, the system rules are constructed based on the reference materials, there would be some missing or misunderstanding during the conversion/transformation from linguistic information from books to digital representation. Hence, the structure of the FPN model can be firstly trained to have a fine-tuned structure. This process would also need lots of realistic and practical case data in order to simulate the real cases. Obviously, the training for model structure can then give us a clearer and visible picture for our complex body structure.

As mentioned before, collecting realistic historical medical report for Chinese medicine is really time-consuming. To reduce the processing time, the raw information should be first having a well-organization and classification. With the fundamental concept of Chinese medicine, a healthy human body is maintained by the balance of each part of the organs. Hence, the data pre-processing can be formed by this condition.

Finally, the suggested model can be also tested for different problem sets. Not only applying the model on the Chinese medical knowledge, this model should also be applied on the western medical knowledge. It could be helpful to give some insight to more researchers, so that the model can be improved from different environment. To be extended, it can be also applied to various practical problem cases, not just only for medical knowledge.

5.3 Future Research Aspect

We have introduced a new interpretation on the concept of **certainty** in this work. This concept is one of the crucial criteria on determining the final conclusion during the problem analysis. Therefore, **certainty** should have a clear and bright position in the FPN model. The crucial function and the ultimate goal of artificial intelligence is to model/simulate human thinking. Thus, to result such a model, we should investigate the thinking process of human body. **Certainty** must be one of the determining factors in human's thinking.

The idea of the new component - *dynamic certainty factor* can be continuously undergone further research. Indeed, this idea is still very fresh and not yet well-developed, thus much more AI techniques could be used for testing and reviewing. If this usage of *dynamic certainty factor* is more mature, there are still many methods to model this **variable**. We believe that a good and mature model could improve the performance and give a clear and simple structure for understanding.

Another research direction could be the evolution of other factors in the current FPN model. Besides the *certainty factor*, researchers can also try to work on other parts of the current model. Indeed, the current model is already a reasonable one in many application practically, there are still many research potentials in the modifications of the current model, discovering new structures or even introducing new components in the model. Although the result may not be the best model eventually, it is still an interesting topic on reviews the thinking/processing path of people's analytical mind. This direction perhaps could give an insight to medical research area at the same time.

The computerization of human intelligence, becoming perfect artificial intelligence absolutely, is a long-term, challenging and exciting task. We believe that our work may be just a start-up in this research area. Besides, the rapid development tread of the techniques can give the advantages on this massive calculation work. Moreover, we wish much more interesting parties would participate and continue this fascinating research direction.

Appendix

Appendix A

Data Details

Body	Tongue Color	Tongue Texture	Faces Texture	Pulse	Constipation
0.2375	0.6838	0.5784	0.6098	0.6438	0.6142
0.4624	0.4875	0.4538	0.3986	0.4144	0.6685
0.5078	0.5620	0.3722	0.3618	0.6898	0.6547
0.4036	0.5888	0.7361	0.6298	0.5574	0.6522
0.5720	0.4330	0.5695	0.4100	0.5957	0.5026
0.8015	0.5153	0.4169	0.6090	0.4327	0.6280
0.4051	0.4599	0.4977	0.7708	0.5278	0.8811
0.8400	0.4943	0.5583	0.6530	0.5559	0.4023
0.1139	0.4001	0.6894	0.6593	0.5016	0.1842
0.4802	0.0425	0.5948	0.4629	0.3176	0.6991
0.2438	0.5594	0.8392	0.3712	0.4667	0.7710
0.3851	0.4703	0.4910	0.4602	0.2497	0.3357
0.1754	0.5265	0.5343	0.7081	0.1857	0.7225
0.5035	0.4364	0.3090	0.8385	0.4967	0.7602
0.3601	0.4795	0.6760	0.2076	0.5716	0.8104
0.5485	0.3006	0.0139	0.7033	0.2392	0.3821
0.5412	0.8125	0.1360	0.7386	0.7361	0.5291
0.2576	0.5477	0.5597	0.5784	0.2490	0.6853
0.5072	0.2615	0.1436	0.7970	0.6574	0.5895
0.8571	0.0379	0.2112	0.2352	0.6191	0.3033
0.9894	0.7903	0.2590	0.9181	0.6500	0.3758
0.5510	0.1812	0.7452	0.8252	0.6542	0.5572
0.8962	0.8366	0.4120	0.8076	0.9954	0.7149
0.9086	0.1196	0.3161	0.6947	0.9457	0.3559
0.3428	0.4917	0.5843	0.5086	0.2620	0.5574
0.1222	0.5376	0.5862	0.2077	0.5904	0.6093
0.0603	1.0000	0.2318	0.5868	0.8376	0.3224
0.3349	0.5878	0.8539	0.7034	0.3490	0.8036

Body	Tongue Color	Tongue Texture	Faces Texture	Pulse	Constipation
0.9513	0.5983	0.3091	0.6813	0.0359	0.5538
0.5125	0.1491	0.6509	0.5777	0.1381	0.5889
0.9903	0.6903	0.1224	0.8225	0.7071	0.3895
0.9895	0.0655	0.4046	0.1733	0.7811	0.1300
0.3450	0.3586	0.1680	0.7906	0.2157	0.3430
0.9073	0.7051	0.1331	0.5683	0.8634	0.3190
0.1867	0.8080	0.1761	0.8593	0.8834	0.4977
0.2641	0.6863	0.6422	0.8601	0.0345	0.5509
0.1583	0.8353	0.0785	0.7676	0.4866	0.1132
0.7942	0.1139	0.1936	0.0369	0.6008	0.4612
0.9707	0.9169	0.1190	0.2647	0.9056	0.4951
0.7846	0.2240	0.4608	0.4189	0.6976	0.5767
0.6607	0.9673	0.9204	0.5610	0.2531	0.6257
0.2308	0.2455	0.0252	0.7127	0.6799	0.2279
0.3489	0.7150	0.0906	0.2620	0.5527	0.3589
0.0740	0.0353	0.0632	0.2804	0.4761	0.2751
0.3060	0.0539	0.6980	0.7991	0.1278	0.3767
0.8238	0.1868	0.9274	0.7105	0.8482	0.2953
0.9647	0.2319	0.3641-	0.3147	0.3844	0.7080
0.9749	0.8780	0.5990	0.3843	0.5771	0.6835
0.7085	0.8199	0.2102	0.6405	0.3370	0.5107
0.5921	0.7892	0.8094	0.4185	0.3080	0.9152
0.2102	0.0728	0.6521	0.2899	0.2868	0.1153
0.6505	0.9611	0.3430	0.8991	0.4922	0.5216
0.4832	0.1506	0.4096	0.3018	0.6679	0.5323
0.5710	0.5593	0.6162	0.7368	0.8923	0.3281
0.2388	0.4203	0.9776	0.5055	0.4802	0.7204
0.2982	0.0176	0.1243	0.1556	0.6214	0.2539
0.6451	0.3562	0.8989	0.6744	0.2265	0.3190
0.7631	0.5254	0.8529	0.3370	0.1840	0.3755
0.0786	0.6582	0.2854	0.3389	0.9742	0.3418
0.8024	0.3913	0.4995	0.0754	0.1397	0.5518
0.5961	0.2539	0.1487	0.5136	0.6325	0.5337
0.8773	0.9629	0.8708	0.2792	0.2482	0.6122
0.0234	0.3834	0.5155	0.1763	0.1295	0.6898
0.4022	0.7135	0.5238	0.9634	0.6310	0.6068
0.5621	0.6574	0.1703	0.3414	0.0804	0.4371
0.6490	0.0792	0.8957	0.0791	0.0844	0.3192
0.2173	0.3776	0.7549	0.9442	0.8998	0.4787
0.6310	0.7479	0.2387	0.4225	0.2148	0.5424
0.7595	0.9648	0.3110	0.4467	0.8196	0.7003

Body	Tongue Color	Tongue Texture	Faces Texture	Pulse	Constipation
0.2929	0.4651	0.0777	0.6349	0.1874	0.3159
0.3524	0.4489	0.6851	0.9987	0.0877	0.3394
0.7886	0.5755	0.4601	0.3295	0.5181	0.7268
0.4533	0.7432	0.5832	0.6471	0.6071	0.3172
0.4403	0.5200	0.8262	0.8141	0.3399	0.6724
0.4299	0.8706	0.1682	0.8138	0.4822	0.5321
0.4734	0.0067	0.9400	0.3777	0.1669	0.1857
0.4368	0.5990	0.7583	0.7593	0.4424	0.8170
0.1204	0.0740	0.4379	0.6113	0.6637	0.1228
0.8995	0.3950	0.2209	0.4514	0.3123	0.7083
0.1876	0.7653	0.8157	0.7294	0.6569	0.8142
0.4191	0.4169	0.4965	0.2579	0.5945	0.8770
0.6786	0.6341	0.2218	0.3632	0.6899	0.5767
0.3358	0.2021	0.7885	0.1820	0.3374	0.6737
0.5679	0.7969	0.6842	0.7929	0.3496	0.5898
0.3626	0.5255	0.5528	0.4587	0.7542	0.3346
0.3191	0.7553	0.5227	0.3881	0.2809	0.6325
0.3080	0.3582	0.1755	0.2314	0.5622	0.2008
0.2407	0.7025	0.3011-	0.6253	0.5938	0.6347
0.4883	0.7861	0.7070	0.3274	0.3121	0.5001
0.2733	0.5366	0.6645	0.3112	0.3821	0.6894
0.7840	0.2524	0.2888	0.6512	0.1757	0.4410
0.3029	0.2968	0.9053	0.4593	0.5714	0.6783
0.6009	0.8088	0.3695	0.4134	0.7601	0.5692
0.5925	0.2423	0.6008	0.8531	0.8169	0.5600
0.7269	0.0129	0.5011	0.3156	0.5172	0.5872
0.4272	0.2926	0.1678	0.8562	0.6683	0.2699
0.7120	0.8912	0.0116	0.4081	0.2192	0.2355
0.5658	0.0479	0.6761	0.1472	0.7206	4.0832
0.2899	0.1858	0.3461	0.8416	0.4653	0.3367
0.5119	0.8784	0.0724	0.1128	0.2757	0.7907

Bibliography

[1] J. Himberg, "A som based cluster visualization and its application for false coloring," in *Proc. of IEEE-INNS-ENNS International Joint Conference*, pp. 587–592, 2000.

[2] D. G. Goodenough, D. Charlebois, P. Bhogal, M. Heyd, S. Matwin, O. Niemann, and F. Portigal, "Knowledge-based imaging spectrometer analysis and gis for forestry," in *Geoscience and Remote Sensing Symposium, 1995. IGARSS '95. Quantitative Remote Sensing for Science and Applications*, vol. 1, pp. 464–467, 1995.

[3] C. Lingenfelder and A. Schmuecker-Schend, "Using knowledge-based methods to administrate an access control system," tech. rep., Heidelberg, 1992.

[4] H. Scarpelli, F. Gomide, and R. R. Yager, "A reasoning algorithm for high-level fuzzy petri nets," *IEEE Transaction. Fuzzy Systems*, vol. 4, no. 3, pp. 282–293, 1996.

[5] L. A. Zadeh, "Fuzzy logic, neural networks, and soft computing," *Communications of the ACM*, vol. 37, no. 3, pp. 77–84, 1994.

[6] S. Zhu and R. G. Reynolds, "The impact of fuzzy knowledge representation on problem solving in cultural algorithms with evolutionary programming,"

in *Genetic Programming 1998: Proceedings of the Third Annual Conference* (J. R. Koza, W. Banzhaf, K. Chellapilla, K. Deb, M. Dorigo, D. B. Fogel, M. H. Garzon, D. E. Goldberg, H. Iba, and R. Riolo, eds.), (University of Wisconsin, Madison, Wisconsin, USA), pp. 801–806, Morgan Kaufmann, 22-25 July 1998.

[7] S. M. Koriem., "A fuzzy Petri net tool for modeling and verification of knowledge-based systems," *The Computer Journal*, vol. 43, no. 3, pp. 206–223, 2000.

[8] R. Günther and H.-P. Lipp, "A fuzzy Petri net concept for complex decision making processes in production control," in *EUFIT'93, First European Congress on Fuzzy and Intelligent Technologies* (H.-J. Zimmermann, ed.), (Aachen, Germany), pp. 290–295, Augustinus Buchhandlung, Sept. 1993.

[9] K.-P. Adlassnig, G. Kolarz, W. Scheithauer, and H. Grabner, "Approach to a hospital-based application of a medical expert system," *Med.Inf*, vol. 11, no. 3, 1986.

[10] K.-P. Adlassnig and G. Kolarz, "Representation and semiautomatic acquisition of medical knowledge in CADIAG-1 and CADIAG-2," *Computers and Biomedical Research, Academic*, vol. 19, 1986.

[11] M. McLeish, "Exploring knowledge acquisition tools for a veterinary medical expert system," in *Proceedings of the first international conference on Industrial and engineering applications of artificial intelligence and expert systems,*

pp. 778–788, ACM Press, 1988.

[12] D. Heckerman, "Probabilistic interpretations for MYCIN's certainty factors," in *Uncertainty in Artificial Intelligence* (L. N. Kanal and J. F. Lemmer, eds.), pp. 167–196, Amsterdam: North-Holland, 1986.

[13] S.-M. Chen, J.-S. Ke, and J.-F. Chang, "Knowledge representation using fuzzy Petri nets," *IEEE Transactions on Knowledge and Data Engineering*, vol. 2, pp. 311–319, Sept. 1990.

[14] M. L. Garg, S. I. Ahson, and P. V. Gupta, "A fuzzy Petri net for knowledge representation and reasoning," *Information Processing Letters*, vol. 39, pp. 165–171, Aug. 1991.

[15] P. J. A. Lever, F.-Y. Wang, and D. Chen, "A fuzzy control system for an automated mining excavator," in *Proceedings of the International Conference on Robotics and Automation. Volume 4* (E. Straub and R. S. Sipple, eds.), (Los Alamitos, CA, USA), pp. 3284–3289, IEEE Computer Society Press, May 1994.

[16] A. Fukayama, M. Ida, and O. Katai, "Behavior-based fuzzy control system for a mobile robot with environment recognition by sensory-motor coordination," in *FUZZ-IEEE'99. 1999 IEEE International Fuzzy Systems. Conference Proceedings.*, vol. 1, (Piscataway, NJ), pp. 105–10, IEEE Service Center, 1999.

[17] E. C. Tsang, J. W. Lee, and D. S. Yeung, "Tuning certainty factor and local weight of fuzzy production rules by using fuzzy neural network," *IEEE Transaction on Systems, Man and Cybernetics*, 2001.

[18] T. Hashiyama, T. Furuhashi, and Y. Uchikawa, "A fuzzy neural network for identifying changes of degree of attention in a multi-attribute decision making process," in *Proc. Int. Joint Conf. Neural Networks*, pp. 705–708, 1993.

[19] T. E. and Y. K., "A fuzzy petri net model for approximate reasoning and its application to medical diagnosis," in *IEEE International Conference on System, Man and Cybernetics.*, pp. 627–631, 1992.

[20] L. A. Zadeh, "Coping with the imprecision of the real world," *Communications of the ACM*, vol. 27, no. 4, pp. 304–311, 1984.

[21] B. R. Gaines, "Fuzzy reasoning and the logics of uncertainty," pp. 179–188, 1976.